Essays in Empirical Corporate Finance:

Author: Francesca Toscano

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ESSAYS IN EMPIRICAL CORPORATE FINANCE

by

FRANCESCA TOSCANO

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by

Francesca Toscano

CO-CHAIR: Professor Thomas J. Chemmanur

CO-CHAIR: Professor Fabio Schiantarelli

ADVISOR: Professor Edith Hotchkiss

ADVISOR: Professor Darren Kisgen

ADVISOR: Professor Zhijie Xiao

ABSTRACT:

After the 2007 financial crisis, a big attention has been dedicated to credit ratings. Whether ratings are capable to provide the most precise and timely information is a question that has been tackled from different angles. The possibility to discipline credit ratings via a regulatory mechanism, the influence that ratings may play on firms' corporate governance decisions and the information they deliver in comparison to other financial intermediaries are the main points that this dissertation aims to address.

The first paper compares the behavior of standard or issuer-paid rating agencies, represented by Standard & Poor's (S&P) to alternative or investor-paid rating agencies, represented by the Egan-Jones Ratings Company (EJR) after the Dodd-Frank Act regulation is approved. Results show that both S&P and EJR ratings are more conservative, stable and, on average, lower after the Dodd-Frank implementation. However, EJR ratings are higher for firms that may generate high revenue for the rater. Additionally, I find that, after the regulation, S&P cares more about its

reputation. Exploiting a measure that captures the bond market's ability to anticipate rating downgrades, I show that, after Dodd-Frank, bond market's anticipation decreases for S&P but increases for EJR, suggesting that S&P ratings are timelier. Finally, I study how the bond market responds to rating changes and how firms perceive ratings in their decision to issue debt in the post-Dodd-Frank period. Results suggest that both S&P downgrades and upgrades generate a greater bond market response. On the contrary, only EJR upgrades have a magnified effect on bond market returns. The greater informativeness of S&P ratings after Dodd-Frank is confirmed by the meaningful impact of these ratings on firm debt issuance.

The second paper (coauthored with Annamaria C. Menichini) studies the relationship between credit rating changes and CEO turnover beyond firm performance. Using an adverse selection model that explicitly incorporates rating change related turnover, our model predicts that a downgrade triggers turnover, more so the lower the managerial entrenchment, but that this relation is weaker when the report provided by the rating agency is more reliable. Our empirical results support these predictions. We show that downgrades explain forced turnover risk, with the new CEO chosen outside the firm that has received the negative credit rating change. In addition, we find that the relation between rating changes and management turnover is stronger when the degree of managerial entrenchment is low, for firms characterized by a high level of investment and for firms less exposed to rating fees. Finally, we show that this relation has weakened in the post-2007 crisis period, in coincidence with the increased reputational concerns of the rating agencies. The results are robust to endogeneity concerns.

The third paper (coauthored with Thomas J. Chemmanur and Igor Karagodsky) focuses on equity analysts, issuer-paid and investor-paid ratings. Equity analysts' forecasts and ratings assigned by issuer-paid credit rating agencies such as Standard and Poor's (S&P) and by investor-paid rating agencies such as Egan and Jones (EJR) all involve information production about the same underlying set of firms, even though equity analysts focus on cash flows to equity and bond ratings focus on cash flows to bonds. Further, the two types of credit rating agencies differ in their incentives to produce and report accurate information signals. Given this setting, we empirically analyze the timeliness and accuracy of the information signals provided by each of the above three types of financial intermediary to their investor clienteles and the information flows between these intermediaries. We find that the information signals produced by EJR are the most timely (on average), and seem to anticipate the information signals produced by equity analysts as well as by S&P. We find that changes in leverage are associated with lower EJR ratings but higher equity analysts' recommendations; further, credit rating changes by EJR have the largest impact on firms' investment levels. We also document an "investor attention" effect (in the sense of Merton, 1987) among stock and bond market investors in the sense that changes in equity analyst recommendations have a higher impact than either EJR or S&P ratings changes on the excess returns on firm equity, while EJR rating changes have a higher impact on bond yield spreads than either S&P ratings changes or changes in equity analyst recommendations. Finally, we analyze differences in bond ratings assigned to a given firm by EJR and S&P, and find that these differences are positively related to the standard proxies for disagreement among stock market investors.

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CHAPTER 1.

DOES THE DODD-FRANK ACT HELP REDUCING THE CONFLICTS OF INTEREST FACED BY CRAS?

1.1 Introduction

"The main goal of the Dodd-Frank Act (Rule 17g-5) is
to discourage issuers from "shopping" for the highest rating and
to encourage credit rating firms to issue more accurate ratings".
(The Wall Street Journal - May 14, 2013)

Credit ratings are an important tool for assessing the relative level of credit risk of a company. More precisely, credit rating agencies provide forward-looking evaluations on the firms' creditworthiness, which benefit both issuers and potential investors. Credit ratings help issuers gain access to debt. Good credit ratings allow them to easily borrow from financial intermediaries or public markets. However, credit ratings also help investors understand the firm's ability to repay its debts.

Disciplining the rating activity is one of the main concerns of regulators in the wake of the 2007 financial crisis. Credit rating agencies (CRAs) have been blamed for contributing to the financial crisis, and the impetus for this idea is the investment-grade, "money-safe" ratings they provided to mortgage-backed securities.

The US Attorney General Eric H. Holder Jr. observed:

"ratings were affected by significant conflicts of interest, and Standard and Poor's (S&P) was driven by its desire for increased profits and market share to favor the interests of issuers over investors."[1]

The conflicts of interest affecting CRAs have their roots mainly on the CRA

[1] Attorney General Eric H. Holder Jr., *The New York Times*, Febrary 3, 2015.

compensation system.[2] The main rating agencies operating on the market are, in fact, paid by the issuers themselves, following a model commonly known as *issuer-paid*. Given the poor performance of CRAs during the financial crisis and the need to better organize the rating industry, in July 2010, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was passed. The law had a precise intention:

> *"to adopt new requirements for credit rating agencies to enhance governance, protect against conflicts of interest, increase transparency to improve the quality of credit ratings and increase credit rating agency accountability".*[3]

The Dodd-Frank Act applies to all the rating agencies that are nationally recognized (NRSROs), independent of the compensation system. However, it is clearly intended to discipline the main rating agencies (Standard and Poor's, Moody's and Fitch) after their misbehaviour during the financial crisis.

The purpose of this paper is to analyze the effects Dodd-Frank had on rating agencies with different business models. More precisely, a comparison between the standard *issuer-paid* model and the alternative *investor-paid* model, where investors demand and pay for ratings, is proposed. This paper is motivated by a large stream of the literature arguing that, among all "financial gatekeepers," credit rating agencies face the most serious conflicts of interest (Partnoy, 2006). Exploiting the potential higher conflicts of interest, many papers (e.g. Jiang et al., 2012, Strobl and Xia, 2012, Cornaggia and Cornaggia, 2013) show that the *issuer-paid* model is slower in

[2] Pagano and Volpin (2010) argue that the conflicts of interest affecting issuer-paid credit rating agencies are due to a combination of three factors: the compensation system adopted, the possibility to sell ancillary services to their clients (like pre-rating assessments and corporate consulting) and the almost total immunity to civil and criminal liability for malfeasance. (Credit ratings should be treated as "opinions" and, because of that, are protected by the First Amendment).

[3] U. S. Securities and Exchange Commission, Press Release, August 27, 2014.

identifying bad news, less timely and, above all, less accurate when compared to the alternative investor-paid model.

This paper exploits the Dodd-Frank Act for five main reasons. First, I want to study whether and how the difference in rating levels between the standard rating agencies, represented by S&P, and the alternative ones, represented by EJR[4], changes after a disciplining law, such as the Dodd-Frank Act. Second, I want to analyze whether and which rating agency is affected more by the passage of the law in terms of rating stability. Third, I want to investigate the reputation effect of the regulation on both rating agencies. In addition, I want to understand whether ratings affect the firm tendency to reduce debt issuance when close to a rating change. Lastly, I aim to investigate the bond market response to rating changes after Dodd-Frank.

The paper is developed by constructing a dataset that includes firm-, bond- and stock-specific information together with rating data. Ratings from S&P and EJR are obtained from different sources. S&P rating data and firm characteristics are collected from Compustat North America. EJR rating data are provided directly by the company. The analysis covers a sample period from 2005 until 2014 to isolate the effects of the Sarbanes-Oxley Act. Following the approach adopted by the literature, the Dodd-Frank period goes from the third quarter of 2010 until the last quarter of 2014.

The results illustrate that the Act lowers corporate credit ratings. Using an ordered logit model, I find that the probability of getting lower ratings from S&P

[4]The Egan and Jones Rating company was founded in 1995 and is wholly investor-supported. It rates the creditworthiness of more than 2000 high-yield and high-grade U.S. corporate debt issuers.

is higher after the regulation is passed. The same result is found for EJR. However, EJR decreases its ratings less, as shown by the rating difference between the two rating agencies that becomes negative after the passage of Dodd-Frank. The study is extended to investigate whether the observed path holds for firms that may be more likely to generate revenue for credit rating agencies.[5] The results show that, before Dodd-Frank, S&P is more likely to inflate ratings for these firms. However, in the post-Act period, there is no longer a tendency to inflate ratings from S&P. On the other side, EJR ratings behave differently. Before Dodd-Frank, EJR does not seem to rate firms with a large volume of bonds more generously than firms with a lower volume. However, after Dodd-Frank, EJR appears to inflate ratings for this category of firms, suggesting a greater attention toward business development and revenue.

My second test examines rating conservativeness and stability. There is no significant difference in the behavior adopted by the two rating agencies.[6]

The third set of results relates to reputation. One way to capture the effect of the Dodd-Frank Act on CRAs' reputation is via bond market anticipation. As suggested by Zuckerman and Sapsford (2001), crises events and financial collapses might

[5] I use two proxies to capture the firm's ability to generate revenue for the credit rating agency. The first is constructed to proxy for *bond issue frequency* (Covitz and Harrison, 2003; Kraft, 2011). The intuition for this proxy relies on the idea that firms issuing many bonds are considered "good clients" for issuer-paid rating agencies. Given the larger business that these firms can offer to CRAs, the phenomenon of rating inflation should be amplified for them. The second proxy (results for this proxy are not tabulated) is borrowed for Strobl and Xia (2012). Their measure of conflicts of interest takes into account the maturity of debt and aims to capture the reliance of firms on credit rating agencies. Their intuition is that firms that have a large proportion of their debt in the form of short-term debt are more subject to the rating agency's evaluation, as they need to roll over their debt more often.

[6] In April 2003, Moody's released a special comment to provide instructions about how to measure the performance of corporate bond ratings. In this document, Moody's tracks several volatility metrics to measure rating stability. Among these: (1) the frequency of rating changes of three or more rating notches and (2) the frequency of rating reversals (defined as rating actions in the opposite direction of previous rating actions). These are *inverse measures of rating stability.*

be exacerbated when investors do not get any warning from outside institutions, including rating agencies, as seen during the Enron scandal. Consequently, issuing timely and accurate ratings becomes fundamental for the investors, who might experience a loss because of the lacking information, and for the institutions themselves, who might be accused of misbehavior. To verify the importance of reputation for credit rating agencies, I test whether the bond market can predict rating announcements by comparing the bond spread variation before the rating disclosure to the bond spread variation afterward. Attention is focused on downgrades, since these are the rating changes that have a greater impact on investors' wealth. I investigate how careful rating agencies are in providing information to the market by examining whether a rating delay occurs for *falling angels*, defined by investment grade firms whose credit rating falls to become speculative, and *large firms*. The analysis of the market's ability to anticipate rating changes is conducted before and after the Act. Results suggest that market anticipation of S&P rating changes falls drastically after the Dodd-Frank Act. The opposite pattern is observed for EJR.

If Dodd-Frank disciplines issuer-paid rating agencies and if, consequently, issuer-paid credit ratings gain greater information content, then we should expect firms to react more to these ratings in terms of their decision to increase/decrease debt issuance. To test this, I verify whether firms' debt issuance is affected more by issuer-paid rating thresholds rather in the post-Dodd-Frank period. Specifically, following the methodology suggested by Kisgen (2006), I study whether debt issuance decreases more when firms receive a plus or a minus S&P rating, compared to a plus or a minus EJR rating. The results suggest that firms with a minus sign assigned by S&P lower their debt issuance more in the post-Dodd-Frank period than firms with a plus or a minus sign from EJR.

The last set of results illustrates the bond market response to rating changes before and after Dodd-Frank. The results suggest that S&P downgrades and upgrades are more informative. The bond market reacts more to EJR upgrades. However, the response to EJR downgrades weakens in the after Dodd-Frank.

Taken together, the results suggest that the two credit rating agencies follow different strategies in the post-Dodd-Frank period with S&P being more prudent, more focused on its reputation and able to exercise a greater impact on the bond market.

This paper contributes to three main areas of research. First, it contributes to the growing literature explaining the differences between rating models that differ for the compensation system adopted. Second, the paper helps to the understanding of factors that may impact the reputation for credit rating agencies. Finally, it enriches the research that studies the effect of government regulations on ratings. To the best of my knowledge, this is the first paper to study the effect of the Dodd-Frank Act on multiple rating agencies and, in particular, to focus on how the difference between issuer-paid and investor-paid rating agencies evolved with a regulatory action. As far as I am aware, the closest paper is by Dmitrov et al. (2014). However, that paper makes no comparison between alternative models for the post-Dodd-Frank period.

The rest of the paper is organized as follows. *Section 2* presents the institutional background with a brief description of the differences between the two alternative models and the reasons that behind the 2010 regulation. *Section 3* contains the literature review. *Section 4* illustrates the underlying theory and the hypotheses tested. *Section 5* describes the data and provides details about the variable construction. *Section 6* presents the main results. *Section 7* concludes.

1.2 CRAs and the Dodd-Frank Act

Before the 2007 crisis, thanks to numerous laws and regulations, credit rating agencies had a primary and often decisive role in defining firm creditworthiness. Supporting that role was the decision in January 2001 from the Basel Committee on Banking Supervision to issue a consultative document on a new Basel Capital Accord (Basel II). Basel II puts great emphasis on external ratings, including from rating agencies, to assess credit risks.

Since 2007, credit rating agencies have been widely criticized because of their generous ratings on mortgage-backed securities and other structured-finance bonds that later defaulted. Critics argue that the observed rating errors underscore features of the rating industry that have weakened rating standards — in particular, the compensation system in which rating agencies are paid by security issuers rather than investors. The financial crisis induced researchers to consider the best compensation model to adopt in the rating industry.

At the moment, the rating market is characterized by two business models.

The first model is the standard *issuer model* where the issuer pays the rating agency for a rating. Many studies have shown that these ratings are more likely to be *inflated* if the issuer is a large or a mature company. These ratings also tend to be inflated during credit booms, since the fee income is more elevated. In addition, the standard model is more likely to be affected by *rating shopping*: issuers shop for the most positive ratings, causing a decline in the rating standards, as agencies hope to avoid losing market share by raising rating scores.

The alternative model is the *investor model* in which there is no direct relationship between issuers and rating agencies. In this model, investors pay the rating agency for an evaluation of the firm they want to invest in.

The weaknesses of the standard model and the role that standard rating agencies had in the financial crisis brought about calls to better discipline the rating industry.

Introduced in the House of Representatives as "The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2009" by Barney Frank and in the Senate Banking Committee by Chris Dodd on December 2, 2002, the Dodd-Frank Act was officially signed into law by President Barack Obama on July 2010. The 2010 Dodd-Frank Act incorporates a wide range of provisions to reshape the rating industry: The most relevant reforms include (1) new authority for the Securities and Exchange Commission (SEC) to suspend or revoke a rating agency's registration if warranted or to penalize individual agency employees for misconduct, (2) public disclosure of the assumptions and data used to arrive at each rating, (3) rules to strengthen corporate governance and board independence, (4) use of look-backs when agency employees leave to join firms whose ratings they may have influenced, (4) creation of an Office of Credit Ratings within the SEC to administer regulation and conduct annual examinations, (5) definition of standardized ratings to ensure comparability across ratings. The Dodd-Frank Act's impact on the rating industry was strengthened by the Franken Amendment (Section 939F) whose main actions aim to "direct the Security Exchange Commission to conduct a study of the credit rating process for structured finance products and the conflicts of interest associated with the issuer-pay and the subscriber-pay models" and to "consider potential mechanisms for determining fees together with alternative compensation models".[7]

Dodd-Frank applies to all the nationally recognized statistical rating organizations (NRSROs). Among all the credit rating agencies operating in the rating sector, there are nine NRSRO rating agencies: Standard & Poor's, Moody's Investors Service, Fitch Ratings, Kroll Bond Rating Agency, A. M. Best, Dominion Bond Rating Service (DBRS), Japan Credit Rating Agency, Egan-Jones Rating Company (EJR) and Morningstar. The Egan-Jones Ratings Company is the only NRSRO rating agency following the investor-paid model.

1.3 Literature Review

This paper relates to three main streams of the literature on CRAs.

First, this paper contributes to the literature that seeks to investigate the reasons behind rating mistakes and perverse rating outcomes, by conducting a comparison between different business models.

Who pays for a rating matters. Jiang et al. (2012) provide evidence from the 1970s when Moody's and S&P were using different compensation systems. In particu-

[7] "Report to Congress on Assigned Credit Ratings", Security Exchange Commission, December 2012.

lar, from 1971 until June 1974, S&P used an investor-paid model, while Moody's used an issuer-paid model. During this period, Moody's ratings systematically exceeded those of S&P. After S&P adopted the issuer-paid model, S&P ratings essentially matched Moody's.

The adoption of a specific compensation model is likely to affect the probability of credit rating inflation. Camanho, Deb and Liu (2012) develop a theoretical model to analyze the effects of competition on the conflicts of interest arising from the issuer compensation model.[8] Their main findings suggest that rating agencies following the issuer-paid model are more likely to issue inflated ratings, as issuers can choose among different agencies. A similar conclusion is presented in Strobl and Xia (2012). Here, the authors show that S&P is more likely to provide higher ratings than EJR when firms have a higher percentage of short-term debt, when firms have less concentrated business relationships with S&P and when firms have appointed a new leader and thus are more inclined to change their operational and financial strategy. On the contrary, no evidence for such behavior is found for EJR. Finally, a more direct comparison between models in the rating industry is offered in a recent paper by Xia (2014). Consistent with Cornaggia and Cornaggia (2013), Xia finds that issuer-paid ratings are slower in reflecting news to the market and incorporate less information when compared to investor-paid ratings. Additionally, Xia finds that issuer-paid rating agencies benefited from the entry of an investor-paid rating agency like EJR, as it

[8] The disciplining effects of competition on credit rating agencies are studied theoretically by Mathis et al. (2009), Camanho et al. (2010), Bar-Isaac and Shapiro (2011), Skreta and Veldkamp (2011), Bolton, Freixas, and Shapiro (2012) and Manso (2013) among others. On the empirical front, Becker and Milbourn (2011) find evidence that the entry of Fitch led to better ratings. The opposite results are reported by Doherty et al. (2012) in their analysis of entry into insurance market by A.M. Best.

brought indirect competition with the issuer-paid raters, revealing the low quality of existing ratings.

Second, this paper relates to the literature analyzing the reputation concerns of credit rating agencies. Covitz and Harrison (2003) analyze whether CRAs act to protect their reputations as delegated monitors. Considering a sample of rating transactions from 1997 to 2002, they show that CRAs care about their reputation and issue timely ratings that can hardly be anticipated by the bond market. Mathis et al. (2009) argue that reputation matters only if a large fraction of CRA income comes from other sources besides rating products. Becker and Milbourn (2011), instead, show that CRA reputation depends on competition. Using the Fitch's market share as a proxy for increased competition, the authors point out that rating quality decreased after the entry of Fitch in the rating market.[9] Lastly, Bar-Isaac and Shapiro (2010) highlight the link between CRA reputation and economic fundamentals varying over the business cycle. Their evidence suggests that CRAs are more likely to issue inaccurate ratings during booms than during recessions.

Third, this paper aims to contribute to the literature that studies the effects of government regulations on credit rating agencies. A first effort in this direction is provided by White (2009), who investigates the potential effects associated with the expanded regulation on credit rating agencies after the optimistic ratings of subprime residential mortgage-backed securities. White points out that excessive regulation may raise barriers to entry, rigidify procedures and discourage innovation in gather-

[9] The result provided by Becker and Milbourn (2011) contradicts the main findings of Bae et al. (2013) and Cheng and Neamtiu (2008).

ing and assessing bond information. A different approach is adopted by Kisgen and Strahan (2010) who examine the impact of ratings regulation on bond yields. Their analysis, which is conducted exploiting a quasi-natural experiment, the NRSRO designation received by DBRS in 2003, shows that investors care about the ratings granted and that they decide to hold bonds only when they are rated investment grade by one or more NRSROs. A similar study with a greater attention toward the investor-paid model is that of Bruno et al. (2015). Here the authors show that the information content of EJR ratings does not change after the NRSRO certification has been assigned, with both upgrades and downgrades being equally likely. A similar analysis is performed by Behr et al. (2014). They analyze the effect of the NRSRO status granted in 1975 on the largest rating agencies. They highlight a sort of "rating entrenchment" for all those rating agencies designated as NRSRO. The designation resulted in more barriers to entry in the industry, lower incentives to improve credit quality and, consequently, higher ratings and reduced rating informativeness.

The first paper to analyze the effects of the Dodd-Frank Act on credit rating agencies is by Dimitrov et al. (2014). The aim of this paper is to investigate whether the passage of the Dodd-Frank had a disciplining effect on CRAs after the 2007 financial crisis. The results suggest that, after Dodd-Frank, the accuracy of rating standards, as measured by the rating levels, the number of false warnings and the information content of rating changes, declines. As a consequence, they conclude that the Dodd-Frank regulation had a weak effect on the rating sector.

The purpose of this paper is to take a step further than Dimitrov et al. (2014) and to better identify the effects of the regulation across different business models.

The goal is to investigate whether Dodd-Frank disciplined issuer-paid rating agencies and how that affected the behavior of a rating agency, like EJR, that benefited of a good reputation in the past.

1.4 Theory and Hypothesis Development

In this section, I briefly discuss the underlying theory and the hypotheses for the empirical tests.

The first rating agency I examine is Standard and Poor's. This is a standard rating agency, paid by issuers and strongly criticized during the 2007 financial crisis for being too lax. The alternative approach, represented by the Egan-Jones Ratings Company, entails a more active role of the investors, who demand and pay for the ratings of the firms. This alternative rating model is widely recognized for being less exposed to conflicts of interest. Several papers have shown the existence of a gap between the standard and the alternative model, which translates into more diligence by the latter. Little has been done to investigate how this gap evolves after the passage of a disciplining regulation like the Dodd-Frank Act.

The comparison between the issuer-paid model and the investor-paid model is conducted around several hypotheses.

First, the Dodd-Frank Act may affect rating levels. In the standard business model, issuing higher ratings is a way for the rating agency to strengthen its relationship with its clients. However, this strategy may hurt the informativeness of ratings.[10] A bad quality firm might receive a good grade only because there is a long-term relationship between the issuer and the rating agency. For this reason, it becomes interesting to analyze whether Dodd-Frank affects the rating level of the standard model compared to the alternative one. I expect S&P to issue lower ratings after the law. The behaviour of EJR needs to be better tested empirically. Different outcomes are, in fact, possible. Given the regulatory pressure created by the Dodd-Frank Act, it might be the case that EJR lowers its ratings as well. However, since Dodd-Frank mainly aims to discipline the issuer-paid rating agencies, EJR may lower its ratings but to a lower extent. Another possibility for EJR is to not change the rating strategy at all. If EJR is confident about its ratings and the market recognizes their informativeness, then EJR should be only marginally affected by Dodd-Frank in terms of credit rating levels. Put differently, the rationale behind the first test is to understand whether the difference between S&P and EJR rating levels becomes negative after Dodd-Frank. This is the first hypothesis (**H1**) I test.

Second, as emphasized by Dmitrov et al. (2014), Dodd-Frank may have a threatening effect on rating agencies. Standard rating agencies may react to the regulation by issuing more *conservative* ratings, meaning by assigning more severe ratings to firms that are not close to default. Following the same logic, ratings are expected to be more *stable*. Stability in ratings is a preferable condition in the rating industry since it ensures a constant flow of information to investors. Given the disciplining effect of the regulation, I expect S&P to adopt a strategy that compensates

[10] As stated by Pagano and Volpin (2010): Ratings inflation and low informativeness may reinforce each other. To the extent that investors are rational, they will see through CRA's incentives to inflate ratings and therefore will consider them as relatively uninformative".

its previous negligence. The effect on EJR is uncertain. I expect EJR not to change its behaviour or, on the limit, to issue more conservative and stable ratings in line with what is suggested by the Dodd-Frank Act. This is the second hypothesis (**H2**) I test here.

Third, disciplining regulations may affect how much rating agencies care about their reputation. Measuring reputation is not easy and the literature has proposed several ways. One way to capture the attention of rating agencies toward reputation is to study whether rating changes can convey information that is not otherwise available to the market. Using the approach of Covitz and Harrison (2003), reputation is proxied by the degree of market anticipation[11], which has clear implications for the reputation of rating agencies. I expect rating agencies to be positively affected by the regulation in terms of reputation. That is, I expect market anticipation to decrease and, on the limit, to become negative after Dodd-Frank. In addition, I expect to observe a magnified effect for S&P compared to EJR. This is the third hypothesis (**H3**) that I test.

My fourth hypothesis relates to how firms perceive credit ratings after Dodd-Frank. If S&P ratings become more reliable after Dodd-Frank, firms should take more into account S&P credit ratings in their decisions regarding debt issuance. Specifically, I expect firms to reduce their debt issuance more after Dodd-Frank when the rating they receive has a plus or a minus S&P rating. There should be no significant

[11] The intuition behind bond market anticipation as a proxy for CRA reputation is the following: if the poor performance of a given firm is somehow anticipated by the market without relying on credit ratings, then credit ratings become meaningless, and rating agencies do not properly act as delegated monitors.

change in how firms perceive EJR ratings after Dodd-Frank Act. This is the fourth hypothesis (**H4**) I test.

The last hypothesis (**H5**) to consider is the market perception of rating changes. If following a downgrade (upgrade), the bond market reacts by strongly decreasing (or increasing) the average market return, then it means the market believes in the information content of rating changes. On the other hand, if the market reaction is weak, the informativeness of credit ratings is reduced. I expect the Dodd-Frank Act to influence the way the bond market responds to rating changes. Specifically, I expect to see a more pronounced market reaction following S&P rating changes. No significative change, for the reasons explained above, should be observed for EJR.

1.5 Data: Sample Selection and Variable Construction

My paper relies on several datasets.

The S&P long-term credit ratings are obtained from Compustat North America Ratings. All the observations for which there are no rating data are deleted from the sample. Following the existing literature, I assign numerical values to each rating on notch basis: AAA=23, AA+=22, AA=21, AA-=20, A+=19, A=18, A-=17, BBB+=16, BBB=15, BBB-=14, BB+=13, BB=12, BB-=11, B+=10, B=9, B-=8, CCC+=7, CCC=6, CCC-=5, CC=4, C=3, D=2, SD=1. Since firm characteristics are available only quarterly, I construct a quarterly time series for the S&P rating database. To this end, I average the rating actions happening in the same quarter, meaning that, if there is more than one rating action in the same quarter, I take the average of these ratings based on the above numerical conversion.

The EJR database is obtained directly from the Egan and Jones Ratings Company. The database contains issuers' names, tickers, rating actions, including new rating assignments, upgrades and downgrades and related rating dates. This database is constructed on a time-series basis, where each credit rating with a rating action is treated as an observation. I thus construct a quarterly time series for the EJR database, where I assign a rating in the current quarter equal to the rating in the previous quarter if no rating action has occurred. Since EJR and S&P use the *same* rating scale, I use the same numerical conversion adopted for the S&P database. As before, I delete observations when rating data are not available. The sample period covered by the EJR dataset goes from 1999 until 2014. I merge the S&P and EJR databases using the firm ticker and the year-quarter information.

Issuers' financial information and firm-specific characteristics are obtained from the Compustat database. I consider characteristics that may have an impact on the rating level. Specifically, I consider size, tangibility, market-to-book, profitability, long-term leverage, debt issuance and cash-asset ratio.[12] To deal with possible endogeneity problems, all variables are lagged one period. All missing values are deleted from the sample. Additionally, to limit the effects of outliers, all the control variables are winsorized at the 1% level. The Compustat database is merged to the S&P and EJR rating database by using the firm ticker and the year-quarter information.

Finally, the analysis requires the use of bond data. Bond information is gathered from FINRA's Trade Reporting and Compliance Engine database (TRACE).

[12]More details about how variables are constructed are provided in the appendix.

This database contains information about bond prices, returns, yields and years to maturity. To get bond spreads, I collect the Treasury yields[13] from the US Treasury database, available online. I construct bond spreads for each firm as the difference between the bond yield of each security and the Treasury yield with comparable maturity and coupon. I drop observations if the spread is equal or lower than zero or if there are missing data.[14]

Figure (1) provides an illustration of the S&P and EJR average credit rating levels over time, starting from 1999, when the EJR ratings became publicly available. The figure shows that the S&P credit ratings are above the EJR credit ratings during the 2007 financial crisis. However, starting from 2010, this trend is reversed. The analysis in this paper starts in January 2005 to isolate the effect of the Sarbanes-Oxley Act. The beginning of the post Dodd-Frank period is July 2009.

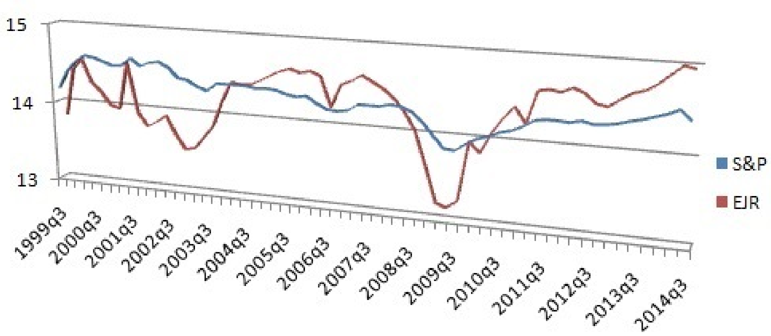

Figure 1: *S&P and EJR rating levels over time*

Summary statistics for firm characteristics and rating data, before and after

[13] Treasury yields are interpolated by the Treasury from the daily yield curve, which relates the yield on a security to its maturity based on the closing-market bid yields on actively traded Treasury securities in the over-the-counter market. The yield values are read from the yield curve at fixed yearly maturities: 1, 2, 3, 5, 7, 10, 20, 30 years.

[14] Further details about the construction of the bond-related data are provided later in the empirical section.

Dodd-Frank, are provided in Table (1.1).

[Insert Table 1.1]

Firm characteristics are almost unchanged after the passage of the Dodd-Frank Act. The market-to-book and tangibility are slightly lower. Size and long term leverage are slightly larger. The credit rating difference, defined as the difference between Standard & Poor's ratings and EJR ratings, is positive before the passage of Dodd-Frank Act but negative afterward. As shown in the summary statistics table, the sample covers 790 firms in the pre-Dodd-Frank period and 699 in the post-Dodd-Frank period. The total number of observations in the pre-Dodd-Frank period is 9,806. The total number of observations in the post Dodd-Frank period is 7,889.

The distribution of rating changes, upgrades and downgrades, for S&P and EJR is provided in Table (1.2).

[Insert Table 1.2]

Table (1.2) illustrates how the rating activity evolves with the passage of the law. It points out that the rating activity has become faster after the regulation is passed. The number of rating changes substantially increases after 2010, with the upgrades becoming more frequent, above all for EJR.

1.6 Empirical Results

1.6.1 Rating Levels

The main purpose of this paper is to analyze how credit rating agencies behave after Dodd Frank Act. The first step (*Hypothesis 1*) is to consider the effect of the Dodd-Frank law on credit rating levels for Standard and Poor's and Egan-Jones. The evidence suggests that rating agencies shifting from the investor model to the issuer model have issued higher ratings over time (Jiang et al., 2012) and that, under specific circumstances that may enhance the conflicts of interest, issuer-paid agencies provide higher ratings than investor-paid rating agencies (Strobl and Xia, 2012). However, we do not know whether this trend persists after a disciplinary regulation, like Dodd-Frank, has been approved. The intuition suggests that S&P should progressively lower its ratings in an attempt to be more prudent after Dodd-Frank. On the opposite side, the result for EJR is an open question. As pointed out in the "Theory and Hypothesis Development" section, different scenarios are possible. One possible result could be EJR issuing lower ratings. However, given that the law was thought to discipline the standard issuer-paid rating agencies, we should expect a more mitigated effect on the alternative investor-paid model. Another possibility for EJR is not to change its strategy because it was already precise and punctual. The last possibility for EJR is to issue higher ratings in the post-Dodd-Frank period. The law, conceived for the standard issuer-paid rating agencies, may have weakened the rating standards for the alternative model. In other words, since the law targets the standard rating agencies, institutions may pay less attention to monitoring all rating agencies, and the investor-paid agencies may, as a result, relax their standards.

I test *Hypothesis 1*, the effect of the Dodd-Frank law on rating levels and, consequently, on the rating difference between S&P and EJR, by estimating the following ordered logit model (or ordinary least squares model) where the dependent variable, the rating level for S&P or EJR, is estimated controlling for specific firm characteristics and a time trend.

More in detail:

$$(S\&P\ Rating)_{it} = \alpha + \beta_1\ Dodd\ Frank\ Act + \beta_2\ X_{it-1} + \beta_3\ Recession + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.1}$$

$$(EJR\ Rating)_{it} = \alpha + \beta_1\ Dodd\ Frank\ Act + \beta_2\ X_{it-1} + \beta_3\ Recession + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.2}$$

where the dependent variable in models (1.1) and (1.2) is represented by the rating scores assigned by S&P and EJR, respectively. Following the methodology used by Dmitrov et al. (2014), I define Dodd-Frank using a dummy variable that takes value one starting from July 2010. I include firm-specific variables that may affect the rating level (size, cash ratio, tangibility, market-to-book ratio, past profitability, past debt issuance ratio, long-term leverage[15]), a dummy variable that accounts for the 2007 financial crisis and a time trend. Results for the S&P and EJR rating levels are presented in Table (1.3).

[Insert Table 1.3]

[15] To account for possible endogeneity issues, all the control variables are lagged one period.

In Table (1.3), Columns (1) and (2) show results when the dependent variable is the S&P rating level. Columns (3) and (4) show results when the dependent variable is the EJR rating level. Columns (1) and (3) present estimates when the model is an ordinary least square, with a time trend and industry fixed effects. Columns (2) and (4) present results when the estimated model is an ordered logit, with a time trend and industry fixed effects. Results are consistent across different specifications.

In the post-Dodd-Frank period, the probability of receiving lower ratings from S&P is higher. All the controls included in the regression have the predicted signs: larger and profitable firms, that issued large amounts of debt in the past and that are characterized by important growth opportunities (as proxied by the market-to-book ratio) are more likely to receive higher ratings. On the contrary, firms with high levels of leverage or with higher cash ratios receive lower ratings. Interestingly, the time trend moves in opposite direction with respect to the coefficient for the post-Dodd-Frank dummy. The time trend suggests that moving from one quarter to the other (i.e. increasing t by one unit) yields an effect of λ on the outcome variable as represented by the rating levels of either S&P or EJR. The positive coefficient for the time trend illustrates that, over time, credit rating levels are increasing. However, as suggested by the *After Dodd-Frank period dummy*, in the post-Dodd-Frank period the probability of getting lower ratings from S&P is lower. Table (1.3), Columns (3) and (4), shows a similar pattern for EJR. EJR assigns lower ratings in the post-2010 period. The control variables have the expected signs.

To understand who responds more by lowering its credit ratings more, I consider the evolution of the rating difference, defined as the cardinal difference between the S&P credit rating and EJR credit rating in the post Dodd-Frank period. The regression I consider is:

$$(S\&P-EJR)_{it} = \alpha+\beta_1\ Dodd\ Frank\ Act+\beta_2\ X_{it-1}+\beta_3\ Recession+\lambda t+\theta_{SIC}+\varepsilon_{it}. \tag{1.3}$$

In model (1.3), the dependent variable is the cardinal difference between the S&P and EJR credit ratings. As before I account for firm-specific controls and a time trend Results are shown in Table (1.4).

[Insert Table 1.4]

In Table 1.4, Columns (1) and (2) describe the evolution of the rating difference in the post-Dodd-Frank period without firm controls but with the inclusion of a time trend. Columns (3) and (4) describe the post-Dodd-Frank rating difference with firm-specific controls. Columns (1) and (3) consider standard errors clustered by firm ticker. Columns (2) and (4) add industry fixed effects.

The results show that the rating difference is declining after Dodd-Frank. To appreciate the magnitude of the results, note Column (4), where the coefficient on the *After Dodd-Frank period*_is negative and equal to (-0.263). This means that, in the post-Dodd-Frank period, S&P issues a rating that is about 0.263 notches lower than EJR. Similar results are found for the other specifications. This implies that both rating agencies issue lower ratings in the post-regulation period, but S&P is more reactive and more prudent, as shown by the diminished rating difference.

One possible concern when estimating the rating difference model (model (3)) is that it does not control for *business cycle dynamics*. The post-regulation period happens during the early stage of the recovery following the 2007 crisis. Different credit rating agencies may react to the uncertainty of the recovery in different ways. Thus it is important to test whether the negative rating difference result still holds while accounting for variables that vary with the business cycle. To test for business cycle implications, I augment model (3) by including the log of GDP, past one-year market returns (using S&P 500 index), S&P 500 index level, perceived firm profitability, industry asset turnover and a proxy for quarterly firm stock market performance. The inclusion of these variables does not change the observed result for the rating difference (Column (5) in Table (4)).[16]

1.6.2 Firms with Conflicts of Interest: High-Fee firms

In the previous paragraph, I have shown that S&P and EJR are both affected by Dodd-Frank in terms of rating levels. They both issue lower ratings, but S&P is more affected and issues lower ratings than EJR. The previous analysis has been conducted by considering all the firms available in the sample. What happens if the sample is restricted to firms that may generate conflicts of interest with credit rating agencies? Specifically, what will be the result in terms of credit rating levels when the analysis focuses on *firms that issue a large number of bonds*? Firms that issue many bonds are more likely to pay higher fees to the credit rating agency. These firms, given

[16] Additionaly, the results are not driven by sample selection issues. They still hold when focusing on firms that exist before and after Dodd-Frank . Specificlly, almost 96% of the firms exist before and after the passage of the Dodd-Frank law.

the frequent relationship with the credit rating agency, can be interpreted as "good clients" in the eyes of standard issuer-paid CRAs. If issuer-paid rating agencies are still affected by conflicts of interest after Dodd-Frank, then we should observe higher ratings from S&P for these categories of firms, compared to other firms, also after the passage of a disciplining regulation. However, if it is true that the Dodd-Frank Act has been conceived to reshape the rating industry, then the lower ratings I observe throughout the entire sample should be observable also for the subset that issues many bonds. No significant change in rating levels should be expected for EJR.

The idea of using the number of bonds issued by every firm as a proxy for potential conflicts of interest is standard in the literature.[17] Examples are Covitz and Harrison (2003), Jiang et al. (2011) and Kraft (2011). To identify firms that issue a large number of bonds, I construct a dummy variable, $High\text{-}Fee$, that takes a value equal to one if the average number of bonds issued by the single firm is greater than the average number of bonds issued by the industry sector to which the firm belongs. To study how the rating levels for S&P and EJR, as well as the rating difference between the two credit ratings ($S\&P - EJR$), change after the passage of Dodd-Frank for firms issuing a large number of bonds, I consider fully interacted models as specified below:

[17] An alternative proxy for conflicts of interest is offered by Jiang et al. (2011). They define a proxy, called "*Low Quality*", which takes value one for firms whose firm's operating margin is below the median operating margin within each year, quarter and S&P credit rating and zero otherwise. The rationale behind this proxy is the following. Firms with a low operating margin within each credit rating bin are the ones more likely to benefit from a higher rating and, consequently, are the ones more likely to generate conflicts of interest. A high rating would, in fact, allow them to get closer to the next rating bin, which makes investors believe that the firm's creditworthiness is about to improve. The analysis for the rating level evolution as well as for the rating difference evolution in the post-Dodd-Frank period for firms classified as Low Quality is not discussed in the body of the paper but is presented in the appendix, Table (1.13).

$$\begin{aligned}\text{S\&P}_{it} = {} & \alpha + \beta_1 Dodd\ Frank + \beta_2 High\text{-}Fee + \beta_3 Dodd\ Frank \times High\text{-}Fee + \\ & + \beta_4 X_{it-1} + \beta_5 X_{it-1} \times High\text{-}Fee + \lambda t + \theta_{SIC} + \varepsilon_{it},\end{aligned} \tag{1.4}$$

$$\begin{aligned}\text{EJR}_{it} = {} & \alpha + \beta_1 Dodd\ Frank + \beta_2 High\text{-}Fee + \beta_3 Dodd\ Frank \times High\text{-}Fee + \\ & + \beta_4 X_{it-1} + \beta_5 X_{it-1} \times High\text{-}Fee + \lambda t + \theta_{SIC} + \varepsilon_{it},\end{aligned} \tag{1.5}$$

$$\begin{aligned}(\text{S\&P-EJR})_{it} = {} & \alpha + \beta_1 Dodd\ Frank + \beta_2 High\text{-}Fee + \beta_3 Dodd\ Frank \times High\text{-}Fee + \\ & + \beta_4 X_{it-1} + \beta_5 X_{it-1} \times High\text{-}Fee + \lambda t + \theta_{SIC} + \varepsilon_{it},\end{aligned} \tag{1.6}$$

Model (1.4) shows the evolution of S&P rating levels across high-fee firms and low-fee firms in the post-Dodd-Frank period. In model (1.4), *Dodd Frank Act* measures the S&P rating level in the post-Dodd-Frank period for firms classified as having low conflicts of interest, meaning firms that issue a small number of bonds compared to the sample mean and, consequently, pay a smaller fee to the credit rating agency. For firms that potentially generate high conflicts of interest, the S&P rating level in the post-Dodd-Frank period is measured by the sum of *Dodd Frank Act* and the interaction variable (*Dodd Frank Act* × *High-Fee*). Thus the interaction variable (*Dodd Frank Act* × *High-Fee*) indicates whether, after the adoption of the Dodd-Frank regulation, S&P ratings change more for firms with a large issuance of bonds than for other firms. A positive coefficient for the interaction variable between *Dodd Frank Act* and *High-Fee* would mean that S&P is inflating ratings more for firms that potentially pay higher fees regardless of the disciplining effect of Dodd-Frank. A coefficient that is not statistically significant should be interpreted as

S&P behaving similarly in his rating activity for high-fee firms and low-fee firms. A negative coefficient for the interaction variable is a signal of greater prudence by S&P also in relation to firms that are larger and issue several bonds. The interpretation holds for the EJR rating levels (model (1.5)) and the rating difference between S&P and EJR (model (1.6)). Results are presented in Table (1.5).

[Insert Table 1.5]

Column (1) considers the S&P credit rating level as the dependent variable, Column (2) the EJR credit rating level and Column (3) the rating difference between S&P and EJR. Columns (1) and (2) present results from ordered logit models and Column (3) presents results for an ordinary least squares model. Each model is estimated by accounting for firm-specific characteristics that may affect ratings, a time trend and industry fixed effects.

The results suggest that, before Dodd-Frank, the probability of assigning higher S&P ratings to firms issuing a large number of bonds is higher (i.e., the probability of S&P inflating ratings for firms able to bring in more revenue is higher). In contrast, EJR does not seem to assume a particular rating strategy regarding this category of firms in the pre-Dodd-Frank period (i.e., it neither inflates or deflates ratings). Combining these results, we observe, in Column (3), that in the pre-Dodd-Frank period the rating difference is positive and equal to (1.846), which implies that S&P tends to assign ratings that are 1.846 notches higher than the ratings that are assigned for the same firm, in the same period, by EJR.

The sum of *Dodd Frank Act* and the interaction variable ($Dodd\ Frank\ Act \times High\text{-}Fee$) provides intuition on the CRAs' behaviour after Dodd-Frank when firms with a large bond issuance are rated. The results suggest that, while S&P is issuing lower ratings for these categories of firms (i.e., the rating inflation phenomenon disappears post-Dodd-Frank for firms that provide a high fee to the credit rating agency), EJR seems to issue higher ratings, generating a rating difference that, as shown in Column (3), is negative. The different behaviour is even more clear when examining the interaction variable ($Dodd\ Frank\ Act \times High\text{-}Fee$). The interaction variable illustrates how S&P and EJR rate *High-Fee* firms relative to low-fee firms in the post-Dodd-Frank period. As shown in Column (1), the interaction variable ($Dodd\ Frank\ Act \times High\text{-}Fee$) is no longer statistically significant. Said in other words, there is no statistically difference between how S&P rates firms that issue many bonds versus those that issue only a few. This is no longer true when considering EJR ratings. Finally, this discrepancy between S&P and EJR ratings becomes more evident in the Column (3). Here, the interaction variable becomes negative and significant at the 1% level suggesting that, after the adoption of the Dodd-Frank Act, S&P reduces its ratings by approximately 0.469 notches in comparison to EJR. While the coefficient for the interaction variable in Column (1) can be explained in light of a more accurate and prudent behaviour that induces S&P to treat high-fee firms and low-fee firms equally, the positive and statistically significant coefficient for the EJR credit ratings is surprising.

The positive coefficient for the interaction variable for EJR could be explained by considering the particular nature of the firms considered in these analysis.

Firms issuing a large number of bonds provide revenue for rating agencies. From the point of view of issuer-paid agencies, they may want to issue higher ratings to cement the relationship with such a client. However, firms that issue many bonds also generate revenue for investor-paid rating agencies. It is, in fact, likely, that an investor that receives a good rating on a firm issuing a large number of bonds will decide to invest again in this firm in the near future. It is, then, likely that the investor will ask updated information about the large issuing firm from paying again the investor-paid rating agency. The tendency of EJR to assign higher ratings for EJR in the post-Dodd-Frank period could be explained in light of the established reputation gained by EJR after the NRSRO certification and the lower monitoring exercised by the Dodd-Frank regulation.[18]

[18] The positive coefficient for the interaction variable (*Dodd Frank Act* $\times$ *High-Fee*) when EJR ratings are studied between high-fee firms and low-fee firms is likely to be driven by the behaviour of the EJR rating company after the NRSRO designation. In order to check if the EJR rating company cares more about *rising revenue* after the NRSRO certification I divide the sample in two sub-samples. First, I consider a sub-sample that goes from January 2005 (the first available date in my data) until July 2010, when the Dodd-Frank regulation was passed. In this way, I can study EJR credit rating levels before and after the NRSRO certification, received by the EJR company in December 2007. Second, I consider a sub-sample that goes from December 2007 until December 2014 (the last available date in my data). In this way, I can study EJR credit rating levels before and after the Dodd-Frank regulation, passed in July 2009, when the NRSRO certification has already been received by EJR. Results are provided in Table (1.14) in the Appendix. By using a fully interacted logit model with respect to High-Fee firms, I get results suggesting that before the NRSRO certification, EJR is more prudent towards this category of firms (i.e. lower probability of assigning higher ratings for firms with a large issuance of bonds). The more cautious behavior of EJR towards these firms might be explained by considering that firms with a large bond issuance are often large firms, more likely to undertake investments and slower in adapting to changing market conditions. Firms with a large bond issuance can, thus, be interpreted as riskier firms, on average. However, after the certification, neither a rating inflation phenomenon or a rating deflation phenomenon is evident in EJR rating activity. Moreover, in the post NRSRO period, EJR is more likely to issue higher ratings for high-fee firms rather than for low-fee firms (i.e. the interaction variable between the *High-Fee* variable and a dummy variable for the post *NRSRO* period is positive). Although the statistical significance of this result is limited at the 10% level, it suggests that, after the certification, the investor-paid rating agency is more worried about generating revenue and, slowly, starts rising rating levels for firms that are potentially more able to generate it. When focusing on the post *NRSRO* sub-sample, the results suggest that after the passage of the Dodd-Frank regulation, the rating inflation phenomenon towards large bond issuing firms is stronger.

1.6.3 Rating Coservativeness and Rating Stability

After considering the evolution of rating levels after Dodd-Frank, the next step of the analysis is to analyze whether there is a threat effect and which credit rating agency is affected more by the regulation in this sense. The threat effect will be disentangled in two effects: the conservativeness effect and the stability effect.

To study the "rating conservativeness", I estimate the following logit model:

$$Warnings_{it} = \alpha + \beta_1 \; Dodd\ Frank\ Act + \beta_2 \; X_{it-1} + \beta_3 \; Recession + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.7}$$

where the dependent variable, *Warnings*, is a dummy which takes a value equal to one if at time (t) the rating assigned is a speculative one but the firm that receives the rating does not default within one year.[19] The dependent variable is, then, regressed against a dummy variable for the post-Dodd-Frank period, firm characteristics, a dummy variable for the 2007 financial crisis and a time trend. Results for S&P ratings and EJR ratings are presented in Table (1.6).

[Insert Table 1.6]

Columns (1) and (2) show results for S&P Warnings. Columns (3) and (4) show results for EJR Warnings. Table (1.6) presents different specifications. Columns (1) and (3) show estimates when standard errors have been clustered by firm ticker, Columns (2) and (4) consider industry fixed effects.

[19] This dependent variable might also be interpreted in a different way. It also captures whether credit rating agencies are becoming more cautious in the post regulation period.

After the regulation is passed, the probability of warnings for S&P increases meaning that the regulation induces S&P to be more cautious and assign a speculative rating although the firm is not close to default. The coefficients associated with the controls suggest that there is a correlation between rating levels and probability of warnings: larger and profitable firms, which are more likely to receive higher ratings are also less likely to receive warnings. On the opposite side, firms with high levels of leverage are more likely to receive lower ratings and credit rating warnings. Summarizing the results from Table (1.3) and Table (1.6), it seems that there is an impact of Dodd-Frank on standard issuer-paid rating agencies, whose evaluations become more prudent.

Similar results are found when considering the last two columns of Table (1.6). EJR appears to issue more conservative ratings. As for S&P, the Dodd-Frank Act has an impact on rating agencies by generating a more prudent attitude.

To investigate the effect on rating stability, I estimate the probability of large rating changes.[20] Credit ratings are expected to change slowly. While unexpected events may require multi-notch rating adjustments, changes in credit quality will typically be reflected in a series of single-notch rating changes spaced out over extended periods. Accurate and stable ratings should quickly incorporate new information,

[20] A special comment released by Moody's in April 2003 states that rating statibility can be proxied in three different ways: the frequency of rating actions, the frequency of large rating changes and the frequency of rating reversals, which refers to the scenario in which a credit rating agency assigns a rating that is subsequently changed and then confirmed again. EJR is characterized by a much larger number of rating changes and rating reversals before and after Dodd-Frank. On the opposite side, S&P is characterized by a lower number of rating changes and rating reversals before and after the law. Since there is no observed variation after Dodd-Frank for the two rating agencies, both in terms of rating changes and in terms of rating reversals, the attention is focused on big rating changes.

anticipate changes in credit quality and adapt to new events in a judicious manner. Large rating changes will thus reflect information that has not been updated and promptly transferred to the market. Specifically, a rise in the frequency of large rating changes, defined as credit rating changes of three or more notches within one year, will be interpreted as a signal of rating instability. The specification I use to test for rating stability is the following:

$$Big\ Rating\ Change_{it} = \alpha + \beta_1\ Dodd\ Frank\ Act + \beta_2\ X_{it-1} + \beta_3\ Recession + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.8}$$

where the dependent variable, *Big Rating Change*, is a dummy that takes a value equal to one if, within one year, the rating from either S&P and EJR, changes of at least three notches. The dependent variable is, then, regressed against a dummy variable for the post-Dodd-Frank period, firm characteristics (previously used), a dummy variable for the 2007 financial crisis and a time trend. Results for S&P and EJR ratings are presented in Table (1.7).

[Insert Table 1.7]

Columns (1) and (2) show results when Big Rating Changes from S&P are taken into account. Columns (3) and (4) show results for Big Rating Changes from EJR. Table (1.7) presents different specifications. Columns (1) and (3) show estimates when standard errors have been clustered by firm ticker, Columns (2) and (4) consider industry fixed effects.

The results suggest that both S&P and EJR show a lower probability of big rating changes after the passage of Dodd-Frank. The result holds independent of the specifications used.

Taken together, the results illustrate that credit ratings are overall more conservative, meaning that CRAs tend to show a more punitive attitude towards issuers, and they are overall more stable, as credit rating agencies regularly monitor firms with the goal of transferring information to the investors.

1.6.4 Placebo Test

One important concern when interpreting the previous tables might be: Is the observed pattern (in terms of credit rating levels, rating conservativeness and rating stability) a result of the reputational loss experienced by credit rating agencies after the 2007 financial crisis? Said differently, the greater caution shown by credit rating agencies after Dodd-Frank might be explained as a reaction to the strong criticism of the rating industry post-2007. If so, how is it possible to disentangle the reputational effects, due to the financial crisis, from the regulatory effects, due to Dodd-Frank? To understand whether my results are a response to the reputational damage or rather a consequence of the Dodd-Frank, a possibility is to run a Placebo Test. This test examines a period that is comparable, in terms of effects on reputation for the credit rating sector, to the one in which Dodd-Frank takes place, but is clearly not affected by any specific regulation for that sector.

To perform the placebo test, one alternative is to consider the post-Enron period. The bankruptcy of Enron Corporation in October 2001 generated massive critiques of rating agencies. Following Covitz and Harrison (2003), to test whether credit rating agencies have reputational concerns following a crisis, it is possible to analyze credit rating agencies' behaviour in fiscal year 2002. This year has few similarities with the post-Dodd-Frank period. First, 2002 is the year following the Enron crisis, which has cast doubts on rating agencies, similarly to what happened post-2007. Second, the 2001 Enron default was followed by a period of economic expansion, like the one experienced after the 2007 financial crisis. My placebo test is described below by the following regressions:

$$(S\&P\ Rating)_{it} = \alpha + \beta_1 Post\text{-}Enron + \beta_2 X_{it-1} + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.9}$$

$$(EJR\ Rating)_{it} = \alpha + \beta_1 Post\text{-}Enron + \beta_2 X_{it-1} + \lambda t + \theta_{SIC} + \varepsilon_{it}, \tag{1.10}$$

$$(S\&P\text{-}EJR)_{it} = \alpha + \beta_1 Post\text{-}Enron + \beta_2\ X_{it-1} + \lambda t + \theta_{SIC} + \varepsilon_{it} \tag{1.11}$$

$$Warnings_{it} = \alpha + \beta_1 Post\text{-}Enron + \beta_2\ X_{it-1} + \lambda t + \theta_{SIC} + \varepsilon_{it} \tag{1.12}$$

$$Big\ Rating\ Change_{it} = \alpha + \beta_1 Post\text{-}Enron + \beta_2\ X_{it-1} + \lambda t + \theta_{SIC} + \varepsilon_{it} \tag{1.13}$$

Equations (1.9) and (1.10) study the rating level behaviour, from either S&P or EJR, in the post-Enron period. Equation (1.11) investigates how the rating difference evolves after Enron's scandal. Equations (1.12) and (1.13) provide intuition for the rating conservativeness and rating stability. In each one of the equations listed above, firm-specific controls are taken into account as well as a time trend and industry fixed effects. Results are provided in Table (1.8).

[Insert Table 1.8]

Columns (1), (2) and (3) describe the rating levels for S&P, the rating levels for EJR and the rating difference between the two agencies after the Enron scandal, respectively. Columns (4) and (5) provide results for S&P and EJR *Warnings* in the post-Enron period. Columns (6) and (7) focus on *Big Rating Changes*.

The results suggest that, after the Enron scandal, credit rating agencies behaved differently than after Dodd-Frank. As shown by Columns (1) and (2), in the period after the Enron scandal, rating inflation for S&P is still evident as shown by a *Post-Enron* dummy that is positive for S&P (i.e., higher probability of getting higher S&P ratings in the post-Enron period) but negative for EJR (i.e., lower probability of getting higher EJR ratings in the post-Enron period). Consequently, the rating difference between S&P and EJR is positive. A closer look at Column (3) shows that the *Post-Enron* dummy is positive and equal to (0.367), suggesting that S&P assigns ratings that are 0.367 notches higher than EJR after Enron's scandal. The different behaviour arises also in the rating conservativeness and rating stability results. Columns (4) and (6) show that S&P ratings are less conservative and stable. A different pattern is found for EJR.

Summing up, the results show that the reputational loss experienced by the credit rating agencies induced a behavior that was not comparable to the behavior observed after Dodd-Frank. In the post Enron period, S&P does not adopt a prudent behaviour, either in the form of lower ratings or in the form of more warnings. Additionally, ratings appear less stable.

1.6.5 Is the Regulation Affecting CRAs' Reputation?

Standard rating agencies, represented by S&P, seem to behave differently from investor-paid rating agencies, represented by EJR. As shown above, in the post-Dodd-Frank period S&P issues lower ratings. On the opposite side, EJR seems to be less affected by Dodd-Frank. A possible explanation might rely on the different effect that the act has on the *reputation* of credit rating agencies. Issuer-paid CRAs suffered more in terms of credibility during the financial crisis and might be more interested in avoiding penalties and protecting their reputation. Such pattern should not be observed among investor-paid CRAs. To investigate whether CRAs' reputation is affected by the regulation and, in particular, whether the regulation affects reputation in different ways according to the business model chosen by rating agencies, I first study which factors may damage more CRAs in terms of reputation and then I analyze whether S&P and EJR care more about their reputation in the post Dodd-Frank period.

1.6.5.a Reputation Hypothesis

Credit rating agencies may act in the interest of issuers or in the interest of investors.

One mechanism for acting in the interest of issuers is to delay rating downgrades.Downgrades have important effects on *issuers*. After receiving a downgrade, the cost of funding becomes higher, contractual obligations tighter and, more generally, reputation deteriorates with significative consequences in the relationships with suppliers. Delaying a downgrade is thus beneficial to issuers. The benefits of delaying are proportional to the magnitude of the downgrade and are generally higher if the costs deriving from the rating change are higher. Costs are magnified if a firm is downgraded from investment class to speculative class, generating what is commonly known as *falling angel*. If such a downgrade occurs, the damage might be serious: firms might be constrained in their access to the capital markets, meaning that getting funds will be possible only after providing proof of enough collateral. In addition, investors might become reluctant to invest in firms whose quality is deteriorating so rapidly. The costs deriving from a downgrade action are important for *large firms*[21], which are generally old firms with a well-recognized reputation on the market. In this circumstance too, delaying a downgrade might be beneficial.

Delaying a downgrade might benefit investors as well if they have already invested in the issuer. A downgrade might, in fact, lower the value of the investor's market portfolio.[22]

However, if delaying a downgrade can help issuers, it can hurt the reputation of rating agencies. If rating actions are delayed, investors might find rating agencies less useful since they cannot anticipate defaults. Reputation costs for rating agencies, in the form of negative publicity, are enhanced when multiple agencies operate on the market. As expected, if there are several agents on the market and one of these is more timely than the others, the costs in terms of reputation and credibility for all

[21] Firm size can be proxied by either the log of total assets or the total number of bonds outstanding. Since it is preferable to have a monthly reputation measure, in this context large firms are firms with a considerable number of bonds issued.

[22] As noted in a report released by the Congress on Assigned Credit Ratings "As with the issuer-pay model, the subscriber-pay model also presents certain conflicts of interest. These conflicts result because subscribers could have an interest in specific credit ratings and, consequently, could exert pressure on credit rating agencies to determine o maintain credit ratings that will result in outcomes that favor the subscriber".

those that delay are worsened. Intuitively, reputation costs because of delayed rating updates become significative when rating changes have an impact on large issuers and when they are responsible for a change of status — from investment to speculative class.

From an empirical point of view, the relative delay of credit ratings may be used to analyze whether firms care about their reputation. If delays increase for falling angels or large firms, then rating agencies are acting without caring much about their reputation. However, if the delays for falling firms and larger firms decrease, then credit rating agencies are acting to protect their reputation and to provide timely and precise information to investors (*Reputation Hypothesis*).

Following Covitz and Harrison (2003), the credit rating delay can be proxied by the degree to which the bond market anticipates the rating change. This measure will be used to study the importance of reputation before and after the introduction of Dodd-Frank. The attention will be focused on downgrades rather than upgrades since delayed downgrades are the rating changes that most likely affect investors and, consequently, rating agency reputation. The capability of the bond market to anticipate rating changes may be a function of several factors, like the magnitude of the rating change or the total spread change in a well-specified time interval around the rating change event. For that purpose, I will consider different variables that may affect market anticipation.

1.6.5.b Market Anticipation: Variable Construction

Bond market anticipation is proxied by the ratio between the corporate bond spread in a well-defined window before the rating change and the corporate bond spread for a longer period that includes the credit rating announcement. More precisely, the *Market Anticipation* variable is defined as:

$$\begin{aligned} Anticipation &= 100 * (Prior\ Period\ Spread\ Change) \ / \ (Total\ Period\ Spread\ Change) \\ &= 100 * \underbrace{(Spread_{t-1} - Spread_{t-i}) \ / \ (Spread_t - Spread_{t-i})}_{Anticipation\ Ratio}. \end{aligned}$$

The frequency for the bond market anticipation analysis is monthly[23], so the subscript t refers to the month of the rating announcement, $t-1$ refers to the month prior to the rating change and i refers to the total number of months taken into account for the event window created around the rating change. If rating agencies are timely and quickly transfer information on the market, then the anticipation ratio should be small and, on the limit, close to zero. However, if rating agencies are slow in identifying credit risk, then the market anticipation ratio should be larger and close to one. As shown in the formula above, the corporate bond spread for the entire period, including the rating announcement, generates the *Total Period Spread Change*.

The methodology used for the construction of the anticipation variable is the following. I consider corporate bond spreads for a six-month window around S&P and EJR rating downgrades. I consider only firms for which I have available data for the five months prior to the rating downgrades. In addition, I assume that each rating downgrade is not preceded or followed by any rating change from either S&P

[23] To estimate the monthly market anticipation, I construct a monthly time series for S&P ratings and EJR ratings following the same methodology explained in the data section.

or EJR other than the one occurring at time t.[24] The assumption is needed to make sure that the spread change is attributable to the downgrade action only.

I drop observations if the total period spread change is less than zero or missing, and I set anticipation between 0 and 100. If anticipation happens to be lower than zero, then it is replaced with 0. However, if anticipation is greater than 100, then it is replaced with 100. Finally, I set anticipation equal to its maximum whenever the total period spread change is negative, equal to or lower than 20 basis points. This assumption relies on the idea that, if the total period spread change is small enough and thus the spread before the rating change is very close to the spread at the time of the rating change, the market is almost fully able to anticipate the rating action and, as a consequence, anticipation can be set equal to its maximum.

1.6.5.c Main Results

The empirical strategy to study the effect of the Dodd-Frank Act on reputation for rating agencies is to regress the market anticipation variable on firm *size* and a dummy variable that identifies *falling angels* while controlling for variables that might affect the anticipation measure. I focus first on the downgrades issued by S&P.

The basic specification is:

[24] Let us assume that we are studying the bond market market anticipation following S&P downgrades in the six-month before the rating announcement. The assumptions needed to make sure that the market is responding only to the S&P rating action are (1) no other rating change from S&P in the five months period before the rating announcement and (2) no rating change for EJR in the entire period.

$$(\text{S\&P Anticipation})_{it}=\alpha+\beta_1\text{Falling Angel Dummy}_{it}+\beta_2\text{Large Client}_{it}+\beta_3\text{X}_{it}+\theta_i+\theta_t+\epsilon_{it}. \tag{1.14}$$

The main variables in the above specification are *Falling Angel Dummy* and *Large Client*. If the sign for β_1 or β_2 is positive, then it means that the market can anticipate the rating action and reputation is a concern for S&P. If the sign is negative, then S&P works properly and the market learns from the information delivered. Model (11) is estimated before and after the passage of the Dodd-Frank Act to check whether there is a change in sign or magnitude for the coefficients of interest. Results are presented in Table (1.9).

[Insert Table 1.9]

Columns (1) and (4) show results when year/quarter fixed effects are taken into account. Columns (2) and (5) add industry fixed effects. Columns (3) and (6) consider year/quarter and firm fixed effects. The first three columns refer to the period before Dodd-Frank. The last three columns refer to the post regulation period. Following Covitz and Harrison (2003), other than the intentional delay proxies, I include a variable that provides information on the magnitude of the downgrades (*S&P Rating Change*)[25], a variable that refers to the years to maturity for each bond considered in the analysis (*Years to Maturity*), the squared total-period spread

[25] SP Magnitude refers to the notch difference before and after the rating change.

change (*Total Period Spread Change*) and the rating scores assigned by S&P (*S&P Rating*). Results indicate that, in the period preceding the regulation, fallen angels are, on average, 14 percentage points more anticipated by the bond market than other downgrades, suggesting that rating agencies are less timely and do not care too much about their reputation. The coefficient associated to falling angels becomes negative when the period after the regulation is taken into account. After the third quarter of 2010, fallen angels are almost 13 percentage points less anticipated than other downgrades. The sign and magnitude of the results seems to suggest that S&P ratings are becoming more timely and less predictable. The coefficient for *S&P Rating Change* is negative and highly significant independent of the specification used or the period considered, suggesting that the market does not anticipate downgrades that are particularly large in magnitude.[26] The coefficient for *Total Period Spread Change*_is negative as expected. *Size, Years to Maturity* and the *S&P Ratings* are not significant.

The basic specification used for EJR rating downgrades is given by:

$$(\text{EJR Anticipation})_{it}{=}\alpha{+}\beta_1\text{Falling Angel Dummy}_{it}{+}\beta_2\text{Large Client}_{it}{+}\beta_3\text{X}_{it}{+}\theta_i{+}\theta_t{+}\epsilon_{it}. \tag{1.15}$$

Results are presented in Table (1.10).

[Insert Table 1.10]

[26] Downgrades that are particularly large in magnitude are often a signal of unstable ratings.

As previously done, I focus my attention on the delay proxies, controlling for factors that may influence the market anticipation of EJR rating downgrades, and I distinguish between pre and post-Dodd-Frank period by adopting different specifications. Results indicate that, in the period preceding the regulation, there is a negative relationship between the delay proxies and the market anticipation variable, suggesting that the bond market cannot anticipate these ratings and predict downgrades. However, after Dodd-Frank, this pattern is no longer true. Falling angels are 8 percentage points more anticipated than common downgrades (when year fixed effects and industry fixed effects are considered). The controls have the expected signs. As before, the coefficient for large clients is not significant. The magnitude of the downgrade (*EJR Magnitude*) is negatively correlated with the market anticipation measure as well as the *Total Period Spread Change.*

The results from Table (1.9) and (1.10) highlight a discrepancy between S&P and EJR in the way they timely report downgrades to the market after the regulation is passed. S&P becomes more timely by issuing ratings whose information would otherwise not be available to the market. EJR rating downgrades appear to be delayed and their information is somehow anticipated by the bond market. Thus the regulation points out divergent behaviors by the two rating agencies.

1.6.6 Information Content of Rating Changes: Bond Market and Stock Market Response

In this section, I compare the reaction of investors to S&P and EJR rating changes before and after the passage of the Dodd-Frank Act. I examine the reaction on the bond market. Using bond data is convenient because bond prices are more affected than stock prices by changes in default probabilities.

The bond market analysis is conducted using the following methodology. Announcement bond returns are calculated for every bond-firm couple in a three-month period that includes the month of the rating announcement (date t, *event date*) the month before the rating announcement (date $t-1$) and the month following the rating announcement (date $t+1$). Announcement bond returns are calculated as:

$$R_{bit} = \frac{P_{bit} - P_{bi(t-2)}}{P_{bi(t-2)}},$$

where P_{bit} defines the price of bond b issued by firm i at the time of the rating change (date t) and $P_{bi(t-2)}$ defines the price of the same bond issued 60 days before the rating change[27] (date $t-2$). Bond returns are calculated as percentage of the bond price two months before the rating announcement to weaken the possibility that the price prior to the rating disclosure has already incorporated part of the bond response to the rating change. I exclude observations if there is more than one rating change in the two months prior to the rating announcement. I drop observations if the rating change at time t is followed by another rating change at time $t+1$.[28]

Results for S&P and EJR rating changes are presented in Table (1.11).

[27] When considering the month following the event date, the announcement bond returns are calculated as:

$$R_{bi(t+1)} = \frac{P_{bi(t+1)} - P_{bi(t-2)}}{P_{bi(t-2)}}$$

[28] The logic behind this procedure is to ensure that bond returns are exposed only to single rating actions.

[Insert Table 1.11]

Table (1.11) shows the bond market response to S&P and EJR rating changes before and after Dodd-Frank. The results show a different pattern before and after the regulation. Following the Dodd-Frank Act, the average bond return after an S&P downgrade is higher in absolute value, although the magnitude of the bond market response is quite small either before or after. Consistently, the average bond return after an upgrade increases. Specifically, the mean return after downgrades is -0.013% before Dodd-Frank and -0.42% afterward. Results are significant at the 1% level. On the opposite side, the mean return after upgrades is 0.067% before Dodd-Frank and 0.47% afterward. The difference is significant at the 1% level. Interestingly, the bond returns following S&P rating changes are not significant before Dodd-Frank, but are afterward.

Additionally, Table (1.11) shows the bond market response to EJR downgrades and upgrades before and after Dodd-Frank. Following an EJR downgrade, the bond market response becomes smaller, with a mean bond return equal to -0.012%, The difference between the mean return in the pre-Dodd-Frank period and post-Dodd-Frank period is equal to 1.64% and is significant at the 1% level. I get slightly different results when bond returns surrounding EJR upgrades are taken into account. The bond market response increases from 1.18% to 1.40%, generating an overall increase of 0.22%, which is significant at the 1% level.

Taken together, the results suggest that the informativiness of credit ratings after the passage of the act is different for the two rating agencies. S&P experiences a greater bond market reaction following any rating change. On the other side, EJR downgrades have a weaker effect. EJR upgrades have a more significant impact on the bond market, but the increase in bond market returns appears to be smaller than the one observed for S&P upgrades.

1.6.7 Real Effects Post-Dodd Frank

One way to analyze the effect of Dodd-Frank on ratings is to consider whether ratings from S&P or EJR are taken into account by firms in their debt issuance. To conduct this analysis, I test whether firms change their debt issuance more after a rating from S&P or after one from EJR. The methodology used resembles the one adopted by Kisgen (2006). The relationship between credit ratings and debt issuance is highly endogenous and suffers of reverse causality. Higher ratings make access to the capital market easier. However, it is also true that firms that issue more debt have greater financing possibilities and may be more likely to receive higher ratings. To address this reverse causality problem, one possibility is to consider credit ratings with a plus or a minus rating. Firms with a plus or a minus credit rating are those close to a change in rating. Given that a change in rating is more likely to happen, to minimize the probability of downgrade (or to maximize the probability of upgrade), firms with a plus or a minus rating will reduce their net debt issuance, relative to their net equity issuance, as a percentage of total assets.

If S&P internalizes the Dodd-Frank regulation and S&P ratings become more reliable, then firms should put more weight on S&P ratings when they decide how much debt to raise. If, as shown in the rating level analysis and in the bond market anticipation analysis, EJR ratings are less timely and more aimed at generating revenue, then the effects of these ratings on firms' debt issuance should shrink after Dodd-Frank.

The model I use to check the effect of ratings on the firm decision to issue debt, before and after Dodd-Frank, is described below:

$$\text{Debt Issuance}_{it}=\alpha+\beta_1\text{S\&P}^{Minus}_{it-1}+\beta_2\text{S\&P}^{Plus}_{it-1}+\beta_3\text{EJR}^{Minus}_{it-1}+\beta_4\text{EJR}^{Plus}_{it-1}+\beta_5\text{X}_{it-1}+\theta_{SIC}+\theta_t+\varepsilon_{it}. \tag{1.16}$$

As in Kisgen (2006), the dependent variable is the net issuance of debt.[29] $S\&P^{Minus}_{it-1}$ and $S\&P^{Plus}_{it-1}$ are dummy variables that take a value equal to one if the S&P rating has a minus or a plus, respectively. EJR^{Minus}_{it-1} and EJR^{Plus}_{it-1} are dummy variables that take a value equal to one if the EJR rating has a minus or a plus, respectively. I control for EJR and S&P rating levels. Additionally, I control for size, profitability, cash ratio, market-to-book and tangibility. Industry and year fixed effects are included. Results are presented in Table (1.12).

[Insert Table 1.12]

Columns (1) and (5) describe the effect on debt issuance of ratings that are on the boundaries within every S&P rating bin as well as within every EJR rating

[29] Debt net issuance is defined as the difference between the change in debt issuance and the change in equity issuance. This difference is thus standardized by total current assets. The change in debt issuance is defined as the change in long-term debt issuance minus long-term debt reduction plus changes in current debt. The change in equity is computed as sale of common and preferred stock minus purchases of common and preferred stock.

bin. Columns (2) and (6) add firm-specific controls (lagged one period). Columns (3) and (7) test for the effects on debt issuance of $S\&P^{Minus}_{it-1}$ and $S\&P^{Plus}_{it-1}$ taken alone, with and without controls, respectively. Columns (4) and (8) test for the effects on debt issuance of EJR^{Minus}_{it-1} and EJR^{Plus}_{it-1} taken alone, with and without controls, respectively. Columns (1) through (4) consider the pre-Dodd-Frank period. Columns (5) through (8) consider the post-Dodd-Frank period. The results show a clear pattern before and after Dodd-Frank. Beforehand, the firm decision to reduce debt issuance is not affected by S&P or EJR ratings. However, debt issuance is affected by S&P ratings after Dodd-Frank, as shown in column (5) through (8). Firms with a minus S&P rating will issue approximately 2.26% less debt net of equity as a percentage of total assets than firms for which no rating change is expected. The magnitude of the reduction in debt issuance is equal to 1.82% when firm-specific controls are added. As shown in columns (5), (6) and (8), there is no effect on debt issuance for firms with EJR ratings with a plus or a minus. The result is consistent with the idea that, after Dodd-Frank, S&P ratings are more reliable, more conservative and more stable. Given the greater attention toward reputation from S&P, firms internalize the improvements in S&P ratings by valuing them more.[30]

[30] I also use an alternative specification that accounts for plus or minus S&P and EJR ratings around the speculative threshold *(BBB+, BBB-)*. The reason to focus on the investment threshold is the significantly lower cost of debt that firms with a rating above the investment threshold have compared to firms below that threshold. Intuitively, the relevance of this threshold should lead to a more pronounced effect on firm debt issuance.

Specifically, I test for:

$$Debt\ Issuance_{it} = \alpha + \beta_1 S\&P^{BBB-/BBB+}_{it-1} + \beta_2 EJR^{BBB-/BBB+}_{it-1} + \beta_5 X_{it-1} + \theta_i + \theta_t + \varepsilon_{it}.$$

$S\&P^{BBB-/BBB+}_{it-1}$ is a dummy that takes a value equal to one if the S&P rating is either BBB- or BBB+. $EJR^{BBB-/BBB+}_{it-1}$ is a dummy variable that takes a value equal to one if the EJR rating

1.7 Conclusion

The Dodd-Frank Act was conceived to reform the rating industry after the the financial crisis. The aim of the Dodd-Frank law is to reduce the conflicts of interest affecting the standard model in which rating agencies are paid by debt issuers. Over time, alternative rating models have been proposed. Among these, researchers have focused a lot on the investor-paid model where investors become intermediaries between the rating agencies and the issuers, reducing the above conflicts of interest. A lot has been done to explain the differences between the two models, but no one has investigated how the two models behave after a disciplining regulation is passed.

In this paper, I show that the Dodd-Frank Act has affected credit rating agencies following different compensation systems in different ways.

The results suggest that the two rating business models adopt different strategies, with S&P being more prudent and threatened by Dodd-Frank. The results highlight that the more cautious behaviour adopted by the issuer-paid CRAs persists in firms able to generate a revenue (i.e., High-Fee firms) . Opposite results are found for the investor-paid CRAs which appear to be more willing to inflate ratings for firms with a greater bond issuance.

Additionally, Dodd-Frank has an effect on CRAs' reputation. Using a market

is either BBB- or BBB+. Firm-specific controls, industry fixed effects and year fixed effects are included. The results (untabulated), illustrate that, before Dodd-Frank, firms with a *BBB-* EJR rating reduce their debt issuance by about 2.69%. The result is significant at the 10% level. However, after Dodd-Frank, the pattern is different. EJR ratings affect less the firm decision to issue debt. On the opposite side, S&P ratings become more relevant after the Dodd-Frank law. Receiving an S&P rating that lies around the investment threshold will cause firms to lower the amount of debt issued by almost 1.4%. The result is significant at the 10% level.

measure for the ability to anticipate rating actions, I notice that there is a greater effort S&P, to provide timely ratings, which can be hardly anticipated by the bond market. On the contrary, bond market anticipation increases for EJR, meaning that the information released by EJR can be easily captured by the bond market without necessarily relying on its ratings. Finally, I check whether the effect of the Dodd-Frank regulation on the two rating models is different from the point of view of the bond market response and the firm ability to reduce/increase debt issuance following credit ratings. My results suggest that the impact of S&P rating changes on the bond market increases after Dodd-Frank. The effect for EJR ratings is ambiguous. Moreover, S&P ratings have a greater effect on the firm decision to reduce debt issuance. EJR ratings have no effect.

This paper represents a first attempt to analyze the effect of government regulations on different business models in the rating industry. It can also be interpreted as illuminating the necessity of viewing the investor-paid model in a different way. For long time, it has been considered the best candidate to replace the standard model. However, my results suggest that it may be necessary to better investigate its role in the market, its growing market share and the credibility of its ratings.

REFERENCES CITED

1. Avramov D., T. Chordia, G. Jostova and A. Philipov, *Credit ratings and the cross section of stock returns*, Journal of Financial Markets 12, 469 - 499.

2. Bae K. H., J. K. Kang and J. Wang, 2013, *Does increased competition affect credit ratings? A reeximination of the effect of Fitch's market share on credit ratings in the corporate bond market*, Forthcoming in Journal of Financial and Quantitative Analysis.

3. Bar-Isaac H. and J. D. Shapiro, 2010, *Ratings quality and the business cycle*, mimeo.

4. Bar-Isaac H. and J. D. Shapiro, 2011, *Credit ratings accuracy and analyst incentives.* American Economic Review (Papers and Proceedings) 101: 120-124.

5. Becker B. and T. Milbourn, 2011, *How did increased competition affect credit ratings?*, Journal of Financial Economics 101, 493-514.

6. Behr P., D. J. Kisgen and J. P. Taillard, 2014, *Did government regulations lower credit rating quality?*, mimeo.

7. Bruno V., J. Cornaggia and K. J. Cornaggia, 2015, *Does regulatory certification affect the information content of credit ratings?*, Forthcoming in Management Science.

8. Camanho N., P. Deb and Z. Liu, 2012, *Credit rating and competition*, mimeo.

9. Cheng M. and M. Neamtiu, 2008, *An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility*, Forthcoming in Journal of Accounting and Economics.

10. Cornaggia J.and K. R. Cornaggia, 2013, *Estimating the costs of issuer-paid credit ratings*, Review of Financial Studies 26, 2229-2269.

11. Covitz D. M. and P. Harrison, 2003, *Testing conflicts of interest at bond ratings agencies with market anticipation: Evidence that reputation incentives dominate*, Finace and Economics Discussion Series (FEDS).

12. Dimitrov Y., D. Palia and L. Tang, 2014, *Impact of the Dodd-Frank Act on Credit Ratings*, Forthcoming in Journal of Financial Economics.

13. Doherty N. A., A. V. Kartasheva and R. D. Phillips, 2012, *Information effect of entry into credit ratings market: The case of insurers' ratings*, Journal of Financial Economics 106: 308-330.

14. Figlewski S., H. Frudman and W. Liang, 2010, *Modeling the effects of macroeconomics factors on corporate default and credit rating transactions*, mimeo.

15. Goel A. and Thakor A., 2011, *Credit ratings and litigation risk*, Navigant Economics and Washington University, Sant Louis, mimeo.

16. Jiang J. X., M. G. Stanford and Y. Xie, 2012, *Does it matter who pays for bond ratings? Historical evidence*, Journal of Financial Economics 105, 607-621.

17. Kisgen D. J. and P. Strahan, 2010, *Do regulations based on credit ratings affect a firm's cost of capital?*, Review of Financial Studies 23, 4324-4347.

18. Kraft P., 2011, *Rating agency adjustments to GAAP financial statements and their effects on ratings and bond yields.*

19. Manso G., 2013, *Feedback effects of credit ratings*, Journal of Financial Economics 109: 535-548.

20. Mathis J., J. McAndrews and J. C. Rochet, 2009, *Rating the raters; Are reputation concerns powerful enough to discipline rating agencies?*, Journal of Monetary Economics 56, 657-674.

21. Pagano M. and P. F. Volpin, 2010, *Credit rating failures and policy options*, Economic Policy, Vol. 25, Issue 62, 401-431.

22. Partnoy F., 2006, *How and why credit rating agencies are not like other gatekeepers*, Chapter 3 in Y. Fuchita and R. E. Litan (eds.), Financial gatekeepers: Can they protect investors?, Nomura Institute of Capital Markets Research, Tokyo, and Banking Institution Press, Washington DC.

23. Skreta V. and L. Veldkamp, 2011, *Ratings shopping and asset complexity: A theory of ratings inflation*, Journal of Monetary Economics 56: 678-695.

24. Strobl G. and H. Xia, 2012, *The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings*, mimeo.

25. White L. J., 2010, *Credit rating agencies and the financial crisis: Less regulation of CRAs is a better response*, Journal of International Banking Law and Regulation 170.

26. Xia H., 2014, *Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?*, Journal of Financial Economics 111, 450-468.

27. Zuckerman G. and J. Sapsford, 2001, *Why credit agencies didn't switch off Enron - S&P cries 'Junk', but the warning comes too late*, The Wall Street Journal, November 29, 2001.

Table 1.1: Summary Statistics - Firm Characteristics and Rating Levels

Means, standard deviations, minimums and maximums for firm-specific characteristics before Dodd-Frank and after Dodd-Frank. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014. Firm-specific characteristics include: Long-Term Leverage, Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Operating Margin, Average Number of Years per firm and Rating Levels (S&P and EJR).

	Before Dodd-Frank				**After Dodd Frank**			
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Long-Term Leverage	0.276	0.148	0.013	0.771	0.285	0.141	0.016	0.773
Size	8.870	1.275	6.151	12.752	9.207	1.304	6.149	12.753
Cash/Assets	0.001	0.031	-0.121	0.125	-0.002	0.03	-0.121	0.124
Tangibility	0.379	0.245	0.006	0.896	0.374	0.262	0.006	0.896
Market/Book	1.495	0.596	0.727	4.097	1.447	0.548	0.727	4.105
Profitability	0.083	0.054	0.003	0.267	0.082	0.051	0.003	0.268
Debt Issuance	0.002	0.031	-0.086	0.211	0.005	0.03	-0.087	0.21
Operating Margin	0.482	0.386	0.007	2.14	0.542	0.41	0.006	2.136
Average N of Years	5.016	1.352	1	6	4.429	0.948	1	5
S&P	14.201	3.432	1	23	14.327	3.204	2	23
EJR	14.178	3.806	2	23	14.632	3.679	2	23
Rating Difference (S&P-EJR)	0.042	2.094	-10	15	-0.291	1.907	-9	12
Years	2005Q1 - 2010Q2				2010Q3 - 2014Q4			
Number of Observations	9806				7889			
Average N of Firms	790				699			

Table 1.2: Rating Changes

Rating changes (upgrades, downgrades and total number of rating changes) from S&P and EJR over the sample period: 2005Q1-2014Q4. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014.

Year	Upgrade S&P	Downgrade S&P	Total S&P	Upgrade EJR	Downgrade EJR	Total EJR
2005	40	45	85	144	92	236
2006	53	97	150	175	173	348
2007	87	89	176	137	177	314
2008	74	96	170	73	322	395
2009	50	138	188	134	248	382
2010	109	60	169	403	79	482
2011	99	45	144	221	124	345
2012	64	49	113	135	157	292
2013	74	46	120	196	125	321
2014	61	25	86	160	63	223

Table 1.3: Rating Levels for S&P and EJR

Ordered Logit Regressions and Ordered Least Squares Regression of S&P rating levels and EJR rating levels on a dummy for the After Dodd-Frank period, firm-specific controls and a time trend. Firms that are contemporaneously rated by S&P and EJR are taken into account. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Long-Term Leverage and Recession. All firm controls are lagged one period. Columns (1) and (2) analyze the evolution of S&P rating levels after Dodd-Frank. Columns (3) and (4) analyze the evolution of EJR rating levels after Dodd-Frank. Columns (1) and (3) show results when the model is an Ordered Least Squares. Columns (2) and (4) show results when the model estimated is an Ordered Logit. Columns (1) through (4) take into account industry fixed effects. All the control variables are winsorized at the 1% level. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	S&P Rating Level		**EJR Rating Level**	
	(1)	(2)	(3)	(4)
After Dodd-Frank period	-0.447***	-0.420***	-0.184***	-0.110**
	(0.0459)	(0.0442)	(0.0540)	(0.0438)
Size	1.093***	1.143***	0.858***	0.846***
	(0.0132)	(0.0151)	(0.0155)	(0.0142)
Cash Ratio	-1.367***	-1.609***	-1.883***	-1.642***
	(0.482)	(0.463)	(0.568)	(0.463)
Tangibles	0.282**	0.352***	-0.242*	-0.204*
	(0.113)	(0.108)	(0.133)	(0.105)
Market/Book	1.529***	1.584***	2.013***	1.933***
	(0.0304)	(0.0318)	(0.0358)	(0.0325)
Profitability	5.613***	5.374***	7.362***	6.040***
	(0.312)	(0.300)	(0.367)	(0.299)
Past Debt Issuance	2.932***	2.530***	4.144***	3.773***
	(0.481)	(0.458)	(0.566)	(0.456)
Long Term Leverage	-6.983***	-6.751***	-9.982***	-8.749***
	(0.126)	(0.133)	(0.148)	(0.137)
Recession	-0.114***	-0.114***	-0.357***	-0.287***
	(0.0421)	(0.0407)	(0.0496)	(0.0404)
Trend	0.0177***	0.0144***	0.0228***	0.0161***
	(0.00198)	(0.00189)	(0.00233)	(0.00190)
N	16799	16799	16799	16799
R^2	0.626	-	0.612	-
Pseudo R^2	-	0.190	-	0.187

Table 1.4: Rating Difference between S&P and EJR

Ordered Least Square Regressions of the Rating Difference between S&P and EJR on a dummy for the After Dodd-Frank period, firm-specific controls and a time trend. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Long-Term Leverage and Recession. All firm controls are lagged one period. Columns (1) and (2) show the evolution of the rating difference between S&P and EJR after Dodd-Frank when a time trend is considerend but no firm-specific controls are added. Columns (3) and (4) show the evolution of the rating difference between S&P and EJR after Dodd-Frank when a time trend is considerend and firm-specific controls are added. Column (1) and (3) assume standard errors clustered by firm ticker. Column (2) and (4) show estimates with industry fixed effects. All the control variables are winsorized at the 1% level. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	(1) S&P- EJR	(2) S&P- EJR	(3) S&P-EJR	(4) S&P-EJR
After Dodd- Frank period	-0.371***	-0.334***	-0.295**	-0.263***
	(0.109)	(0.0384)	(0.118)	(0.0418)
Trend	0.00457	0.00292*	-0.00185	-0.00503***
	(0.00487)	(0.00173)	(0.00525)	(0.00180)
Size			0.154***	0.235***
			(0.0384)	(0.0120)
Cash Ratio			-0.227	0.517
			(0.721)	(0.439)
Tangibles			-0.195	0.524***
			(0.205)	(0.103)
Market/Book			-0.452***	-0.484***
			(0.0798)	(0.0277)
Profitability			-1.683***	-1.749***
			(0.476)	(0.284)
Past Debt Issuance			-1.691***	-1.211***
			(0.494)	(0.438)
Long Term Leverage			2.916***	2.999***
			(0.342)	(0.115)
Recession			0.258***	0.243***
			(0.0593)	(0.0383)
N	17695	17695	16799	16799
R^2	0.007	0.111	0.096	0.193
Clustered by Firm Ticker S.E.	Yes	No	Yes	No
Industry F.E.	No	Yes	No	Yes

Table 1.5: High-Fee firms - Firms with High Conflicts of Interest

Fully interacted models that describe S&P and EJR rating levels post Dodd-Frank for firms classified as High-Fee firms. Columns (1) and (2) show results for ordered logit regressions, with the dependent variable represented by S&P and EJR rating levels, respectively. Column (3) considers the rating difference between S&P and EJR (S&P-EJR). Each dependent variable is regressed against a dummy for the post Dodd-Frank period, a dummy for High-Fee firms, an interaction term between the two and firm specific controls. Firm specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Cash Ratio, S&P and EJR rating levels. All the control variables are winsorized at the 1% level. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Results for debt issuance, cash ratio, tangibility and time trend are not reported.

	S&P	EJR	(S&P-EJR)
Post Dodd-Frank	-0.610***	-0.265***	-0.337***
	(0.0661)	(0.0639)	(0.0655)
(Post Dodd-Frank)×(High-Fee)	0.0526	0.404***	-0.469***
	(0.0803)	(0.0789)	(0.0800)
(High-Fee)	1.194***	-0.270	1.846***
	(0.286)	(0.284)	(0.289)
Size^2	0.0641***	0.0441***	0.0290***
	(0.00182)	(0.00175)	(0.00169)
Size^2×*(High-Fee)*	-0.00737***	0.00283	-0.0154***
	(0.00209)	(0.00207)	(0.00205)
Market/Book	1.713***	2.097***	-0.790***
	(0.0715)	(0.0692)	(0.0668)
(Market/Book)×(High-Fee)	0.364***	0.376***	0.184**
	(0.0888)	(0.0868)	(0.0853)
Profitability	1.243*	3.124***	-3.114***
	(0.676)	(0.652)	(0.668)
(Profitability)×(High-Fee)	4.371***	3.127***	2.111**
	(0.851)	(0.833)	(0.850)
Leverage	-5.900***	-9.342***	5.863***
	(0.290)	(0.284)	(0.278)
(Leverage)×(High-Fee)	-2.675***	-2.259***	-1.179***
	(0.354)	(0.342)	(0.345)
N	8939	8939	8939
R^2	-	-	0.252
Pseudo R^2	0.209	0.215	-
Time Trend	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Table 1.6: S&P and EJR Rating Conservativeness

Logit Regressions to test rating conservativeness after Dodd-Frank. The dependent variable is Warnings. Warnings is a dummy that takes a value equal to one if the rating at time t is speculative but the firm does not default within one year. The dependent variable, Warnings, is regressed on a dummy for the after Dodd-Frank period, firm-specific controls and a time trend. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Long-Term Leverage and Recession. All firm controls are lagged one period. Columns (1) and (2) consider S&P Warnings. Columns (3) and (4) consider EJR Warnings. Columns (1) amd (3) assume standard errors clustered by firm ticker. Columns (2) and (4) show estimates with industry fixed effects. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	S&P Warnings		**EJR Warnings**	
	(1)	(2)	(3)	(4)
After Dodd-Frank period	0.419***	0.399***	0.336**	0.332***
	(0.137)	(0.0714)	(0.134)	(0.0712)
Size	-0.946***	-0.986***	-0.729***	-0.632***
	(0.0802)	(0.0250)	(0.0696)	(0.0231)
Cash Ratio	1.170	1.723**	1.234	2.247***
	(1.058)	(0.733)	(1.097)	(0.766)
Tangibles	-1.064***	-0.590***	-1.159***	0.223
	(0.385)	(0.175)	(0.348)	(0.179)
Market/Book	-1.075***	-1.350***	-1.639***	-2.097***
	(0.154)	(0.0575)	(0.178)	(0.0688)
Profitability	-2.827***	-3.443***	-3.692***	-4.595***
	(0.809)	(0.500)	(0.780)	(0.529)
Past Debt Issuance	-2.271***	-2.658***	-4.841***	-4.850***
	(0.730)	(0.729)	(0.749)	(0.751)
Long Term Leverage	6.009***	7.275***	7.664***	9.440***
	(0.616)	(0.211)	(0.575)	(0.231)
Recession	0.0193	-0.0183	0.152*	0.115*
	(0.0703)	(0.0664)	(0.0796)	(0.0668)
Trend	-0.0189***	-0.0211***	-0.00969	-0.0138***
	(0.00665)	(0.00310)	(0.00640)	(0.00310)
N	16799	16598	16799	16719
Pseudo R^2	0.291	0.406	0.305	0.404
Clustered by Firm Ticker S.E.	Yes	No	Yes	No
Industry F.E.	No	Yes	No	Yes

Table 1.7: S&P and EJR Rating Stability

Logit Regressions to test rating stability after Dodd-Frank. The dependent variable is Big Rating Change.Big Rating Change is a dummy that takes a value equal to one if the rating level, from either S&P or EJR, changes of at least 3 notches in one year. The dependent variable, Big Rating Change, is regressed on a dummy for the after Dodd-Frank period, firm-specific controls and a time trend. The Before Dodd-Frank period goes from January 2005 to June 2010. The After Dodd-Frank period incorporates all rating actions from July 2010 until December 2014. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Long-Term Leverage and Recession. All firm controls are lagged one period. Columns (1) and (2) consider Big Rating Changes for S&P. Columns (3) and (4) consider Big Rating Changes for EJR. Columns (1) amd (3) assume standard errors clustered by firm ticker. Columns (2) and (4) show estimates with industry fixed effects. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	S&P Big Rating Change		**EJR Big Rating Change**	
	(1)	(2)	(3)	(4)
After Dodd-Frank period	-0.682**	-0.765***	-0.267*	-0.364***
	(0.315)	(0.231)	(0.152)	(0.109)
Size	-0.0562	0.0187	-0.0924*	-0.00345
	(0.0993)	(0.0605)	(0.0524)	(0.0300)
Cash Ratio	5.417**	4.962**	0.260	0.890
	(2.497)	(2.248)	(1.576)	(1.049)
Tangibles	-0.485	0.950*	-0.555**	0.349
	(0.426)	(0.523)	(0.236)	(0.256)
Market/Book	-0.566**	-0.676***	-0.486***	-0.681***
	(0.282)	(0.183)	(0.139)	(0.0820)
Profitability	-3.384	-4.691***	0.401	0.131
	(2.376)	(1.577)	(0.915)	(0.706)
Past Debt Issuance	-1.259	-1.016	-2.633**	-2.073*
	(2.576)	(2.176)	(1.200)	(1.092)
Long Term Leverage	3.009***	2.331***	2.370***	2.551***
	(0.855)	(0.502)	(0.426)	(0.253)
Recession	0.313	0.286	0.379***	0.353***
	(0.216)	(0.174)	(0.112)	(0.0896)
Trend	0.0321***	0.0345***	0.0246***	0.0269***
	(0.0122)	(0.0105)	(0.00641)	(0.00481)
N	16799	13700	16799	16696
Pseudo R^2	0.047	0.110	0.036	0.113
Clustered by Firm Ticker S.E.	Yes	No	Yes	No
Industry F.E.	No	Yes	No	Yes

Table 1.8: Placebo Test

Analysis of credit rating levels, rating conservativeness and rating stability in the post-Enron period. The Enron scandal was revealed in October 2001. Post-Enron is a dummy that takes a value equal to 1 in year 2002. Columns (1) and (2) describe the evolution of S&P and EJR rating levels in the post-Enron period. Column (3) shows the rating difference in the post-Enron period. Columns (4) and (5) test for rating conservativeness after the Enron scandal by looking at the probability of Warnings, where Warnings is a dummy that takes a value equal to 1 if the rating at time t is speculative but the firm does not default within one year. Columns (6) and (7) show results for the rating stability test. To this aim, the probability of Big Rating Changes is taken into account, where Big Rating Change is a dummy that takes a value equal to 1 if the rating level, from either S&P or EJR, changes of at least 3 notches in one year. All the regressions are estimated by using industry fixed effects and by adding a time trend. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, Long-Term Leverage. All control variables are one period lagged and winsorized at the 1% level. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Rating Level		**Rating Difference**	**False Warning**		**Big Rating Change**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	S&P	EJR	(S&P-EJR)	S&P	EJR	S&P	EJR
Post-Enron	0.207***	-0.0920**	0.367***	-0.283***	0.206***	0.370**	0.100
	(0.0424)	(0.0424)	(0.0364)	(0.0687)	(0.0665)	(0.181)	(0.109)
Size	0.995***	0.819***	0.148***	-0.874***	-0.694***	0.176**	0.0767
	(0.0228)	(0.0221)	(0.0169)	(0.0364)	(0.0339)	(0.0811)	(0.0493)
Cash Ratio	-3.065***	-2.500***	-0.539	0.981	3.773***	6.936**	1.968
	(0.735)	(0.723)	(0.620)	(1.136)	(1.140)	(2.964)	(1.767)
Tangibles	1.341***	0.708***	0.372***	-0.781***	-0.606***	-0.217	0.349
	(0.146)	(0.145)	(0.126)	(0.244)	(0.235)	(0.631)	(0.383)
Market/Book	1.054***	1.345***	-0.265***	-0.626***	-0.985***	-1.226***	-0.179
	(0.0401)	(0.0416)	(0.0308)	(0.0747)	(0.0806)	(0.300)	(0.119)
Profitability	7.394***	8.514***	-2.664***	-6.969***	-8.263***	-15.41***	-8.839***
	(0.472)	(0.468)	(0.392)	(0.773)	(0.770)	(2.680)	(1.374)
Long Term Leverage	-6.570***	-6.756***	0.965***	7.350***	7.614***	1.711**	2.178***
	(0.190)	(0.190)	(0.146)	(0.300)	(0.300)	(0.684)	(0.421)
Trend	-0.0362***	0.00220	-0.0391***	0.0283***	-0.00168	0.127***	0.0976***
	(0.00444)	(0.00444)	(0.00380)	(0.00717)	(0.00699)	(0.0204)	(0.0115)
Past Debt Issuance	2.534***	2.994***	-0.954*	-3.091***	-4.968***		
	(0.605)	(0.600)	(0.520)	(0.975)	(0.969)		
N	6918	6918	6918	6754	6823	5742	6302
R^2	-	-	0.191	-	-	-	-
Pseudo R^2	0.180	0.175	-	0.379	0.363	0.189	0.141

Table1.9: Bond Market Anticipation around S&P Downgrades

OLS regression of Anticipation on a dummy variable for Falling Angels, Size and various controls. Anticipation is defined as:

$$\begin{aligned} Anticipation &= 100 * (Prior\ Period\ Spread\ Change) \ / \ (Total\ Period\ Spread\ Change) \\ &= 100 * \underbrace{(Spread_{t-1} - Spread_{t-i}) \ / \ (Spread_t - Spread_{t-i})}_{Anticipation\ Ratio}. \end{aligned}$$

The Anticipation variable is constructed by considering a six-month period around any S&P downgrade. The six-month period is constructed by assuming that the rating change observed is the only one that occurs. In the regressions reported above, I assume that EJR ratings do not change over the entire period and S&P ratings do not change in the period prior to the observed change. Falling Angels is a dummy that takes a value equal to 1 if the firm is downgraded from the investment class to the speculative class. Size is proxied by the number of bonds outstanding. Additional controls include: S&P rating change, Years to Maturity, Total Period Spread Change and S&P rating level. Columns (1) and (4) account for year-quarter fixed effets. Columns (2) and (5) account for year-quarter and industry fixed effects. Columns (3) and (6) account for year-quarter and firm fixed effects. Columns (1)-(3) consider the Before Dodd-Frank sample. Columns (4)-(5) consider the After Dodd-Frank sample. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Before Dodd-Frank			**After Dodd-Frank**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Anticipation	Anticipation	Anticipation	Anticipation	Anticipation	Anticipation
Falling Angel	14.30***	14.22***	17.35***	-13.22***	-14.28***	-14.85***
	(2.952)	(3.056)	(3.072)	(3.804)	(4.123)	(3.895)
Size	0.763	0.475	18.97*	-0.302	0.943	12.63*
	(0.803)	(2.146)	(10.16)	(0.860)	(2.672)	(7.383)
S&P Rating Change	-71.80***	-72.42***	-125.8***	-60.16***	-60.85***	-39.15***
	(1.672)	(1.780)	(16.37)	(1.213)	(1.476)	(5.905)
Years to Maturity	0.114	-0.0269	-0.0853	-0.158	-0.0107	0.0878
	(0.0948)	(0.111)	(0.123)	(0.140)	(0.174)	(0.153)
Total Period Spread Change	-9.528***	-8.434***	-8.576***	-17.48***	-14.24***	-15.26***
	(1.080)	(1.101)	(1.203)	(1.808)	(2.069)	(1.886)
S&P Rating	-0.335	0.194	56.37***	0.0904	0.966	-19.98***
	(0.218)	(0.714)	(17.10)	(0.226)	(0.711)	(6.141)
N	644	644	644	818	727	818
R^2	0.849	0.867	0.881	0.820	0.833	0.856
Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	No	Yes	No
Firm F.E.	No	No	Yes	No	No	Yes

Table 1.10: Bond Market Anticipation around EJR Downgrades

OLS regression of Anticipation on a dummy variable for Falling Angels, Size and various controls. Anticipation is defined as:

$$\begin{aligned} Anticipation &= 100 * (Prior\ Period\ Spread\ Change)\ /\ (Total\ Period\ Spread\ Change) \\ &= 100 * \underbrace{(Spread_{t-1} - Spread_{t-i})\ /\ (Spread_t - Spread_{t-i})}_{Anticipation\ Ratio}. \end{aligned}$$

The Anticipation variable is constructed by considering a six-month period around any EJR downgrade. The six-month period is constructed by assuming that the rating change observed is the only one that occurs. In the regressions reported above, I assume that S&P ratings do not change over the entire period and EJR ratings do not change in the period prior to the observed change. Falling Angels is a dummy that takes a value equal to 1 if the firm is downgraded from the investment class to the speculative class. Size is proxied by the number of bonds outstanding. Additional controls include: EJR rating change, Years to Maturity, Total Period Spread Change and EJR rating level. Columns (1) and (4) account for year-quarter fixed effets. Columns (2) and (5) account for year-quarter and industry fixed effects. Columns (3) and (6) account for year-quarter and firm fixed effects. Columns (1)-(3) consider the Before Dodd-Frank sample. Columns (4)-(5) consider the After Dodd-Frank sample. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Before Dodd-Frank			**After Dodd-Frank**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Anticipation	Anticipation	Anticipation	Anticipation	Anticipation	Anticipation
Falling Angel	-9.399***	-7.344***	-9.022***	8.719***	8.162***	9.284***
	(2.040)	(2.089)	(2.114)	(2.932)	(3.026)	(3.080)
Size	1.354***	0.752	-3.745	0.0477	1.854**	-3.057
	(0.219)	(0.628)	(2.707)	(0.247)	(0.754)	(3.221)
EJR Rating Change	-75.53***	-75.46***	-73.37***	-76.41***	-77.08***	-74.30***
	(0.759)	(0.805)	(1.255)	(0.758)	(0.788)	(1.579)
Years to Maturity	-0.0570	-0.0233	0.00281	-0.0529	-0.0996	-0.122
	(0.0550)	(0.0612)	(0.0659)	(0.0799)	(0.0914)	(0.0938)
Total Period Spread Change	-3.520***	-3.460***	-3.197***	-15.78***	-15.72***	-15.64***
	(0.417)	(0.423)	(0.429)	(0.723)	(0.726)	(0.726)
EJR Rating	0.221*	0.375	-1.349	-0.135	-0.264	-3.609**
	(0.126)	(0.266)	(0.983)	(0.0890)	(0.201)	(1.570)
N	3303	3292	3303	3063	3009	3063
R^2	0.840	0.854	0.862	0.815	0.826	0.837
Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	No	Yes	No
Firm F.E.	No	No	Yes	No	No	Yes

Table 1.11: Bond Market Response to S&P and EJR Credit Rating Changes

Bond market returns before and after the Dodd-Frank regulation. Bond market returs are defined as:

$$R_{bit} = \frac{P_{bit} - P_{bi(t-2)}}{P_{bi(t-2)}},$$

P_{bit} defines the price of bond b issued by firm i at the time of the rating change (t) and $P_{bi(t-2)}$ defines the price of the same bond issued two months prior to the rating change (t-2). Bond returns are calculated as percentage of the bond price two months prior to the rating announcement to weaken the possibility that the price prior to the rating disclosure already incorporates part of the bond market response. I exclude observations if there are rating changes in the two months prior to the rating announcement. I drop observations if the rating change at time t is followed by another rating change at time t+1.

	Before Dodd-Frank		**After Dodd-Frank**	
	Obs.	Bond Return (%)	Obs.	Bond Return (%)
Upgrade S&P	2416	0.067	3212	0.47***
Downgrade S&P	1767	-0.013	3504	-0.42***
Upgrade EJR	8347	1.18***	15354	1.40***
Downgrade EJR	7821	-1.65***	7696	-0.012***

Table 1.12: Debt Net Issuance after Dodd-Frank

OLS regression of Debt Net Issuance before and after the Dodd-Frank Act on credit rating dummy variables and firm-specific controls. $S\&P^{Minus}$ and $S\&P^{Plus}$ are dummy variables that take a value equal to 1 if the firm has a plus or a minus S&P rating, respectively, and 0 otherwise. EJR^{Minus} and EJR^{Plus} are dummy variables that take a value equal to 1 if the firm has a plus or a minus EJR rating, respectively, and 0 otherwise. Firm-specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, S&P and EJR rating levels. All control variables are one period lagged and winsorized at the 1% level. Regressions (1)-(4) study the response of firm debt issuance Before Dodd-Frank. Regressions (5)-(8) study the response of firm debt issuance After Dodd-Frank. In columns (1)-(8), a time trend and industry fixed effects are included. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Before Dodd-Frank				**After Dodd-Frank**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Debt Issuance	Debt Issuance	Debt Issuance	Debt Issuance	Debt Issuance	Debt Issuance	Debt Issuance	Debt Issuance
$S\&P^{Minus}$	-0.00708	-0.00700	-0.00651		-0.0226***	-0.0182**	-0.0183**	
	(0.0123)	(0.0121)	(0.0121)		(0.00841)	(0.00815)	(0.00814)	
$S\&P^{Plus}$	0.0120	0.0108	0.00954		-0.00543	-0.00451	-0.00483	
	(0.0116)	(0.0114)	(0.0114)		(0.00808)	(0.00771)	(0.00770)	
EJR^{Minus}	-0.0155	-0.0137		-0.0115	0.000458	0.00528		0.00557
	(0.0113)	(0.0111)		(0.0110)	(0.00831)	(0.00794)		(0.00796)
EJR^{Plus}	-0.00511	-0.00462		-0.00245	0.00888	0.00766		0.00773
	(0.0113)	(0.0110)		(0.0109)	(0.00797)	(0.00759)		(0.00760)
S&P	-0.00647*	-0.00766**	-0.00746*	-0.00758**	-0.0101***	-0.0105***	-0.0105***	-0.00927***
	(0.00346)	(0.00383)	(0.00382)	(0.00377)	(0.00248)	(0.00251)	(0.00250)	(0.00244)
EJR	0.0131***	0.00694**	0.00699**	0.00681**	0.0146***	0.00966***	0.00984***	0.00889***
	(0.00331)	(0.00347)	(0.00346)	(0.00347)	(0.00227)	(0.00226)	(0.00224)	(0.00223)
Size		0.00139	0.000630	0.00135		0.00366	0.00359	0.00363
		(0.00553)	(0.00549)	(0.00548)		(0.00354)	(0.00353)	(0.00354)
Profitability		0.303**	0.298**	0.323***		0.316***	0.316***	0.313***
		(0.125)	(0.125)	(0.124)		(0.0896)	(0.0895)	(0.0899)
Cash Ratio		0.0661	0.0748	0.0720		0.0308	0.0338	0.0389
		(0.0796)	(0.0791)	(0.0794)		(0.0519)	(0.0518)	(0.0519)
Market/Book		0.0222**	0.0223**	0.0207**		0.0204***	0.0203***	0.0210***
		(0.00990)	(0.00990)	(0.00984)		(0.00780)	(0.00778)	(0.00781)
Tangibility		-0.00112	0.00161	-0.00154		-0.0140	-0.0152	-0.000472
		(0.0448)	(0.0446)	(0.0448)		(0.0342)	(0.0342)	(0.0338)
N	532	532	532	532	598	598	598	598
R^2	0.211	0.261	0.259	0.258	0.238	0.319	0.318	0.313
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.13: Low Quality Firms - Firms with High Conflicts of Interest

S&P rating level, EJR rating level and rating difference between S&P and EJR after Dodd-Frank. Dodd-Frank is a dummy that takes a value equal to 1 starting from July 2010 until December 2014. Low quality is a dummy that takes value 1 if the firm's operating margin is below the median within each year, quarter and S&P credit rating and zero otherwise. The firm's operating margin is defined as the operating income before depreciation divided by total assets. Firm characteristics include: Cash ratio, Tangibility, Market to Book, Profitability, Debt Issuance and Leverage. A time trend and industry fixed effects are included in each specification. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	(1) S&P	(2) EJR	(3) (S&P-EJR)
Dodd-Frank	-0.293***	-0.0178	-0.288***
	(0.0475)	(0.0470)	(0.0451)
Low-Quality	0.350***	0.0649	0.171***
	(0.0431)	(0.0425)	(0.0406)
(Dodd Frank)×(Low-Quality)	-0.128**	0.0922*	-0.182***
	(0.0548)	(0.0548)	(0.0525)
Size^2	0.0620***	0.0462***	0.0127***
	(0.000822)	(0.000775)	(0.000652)
N	16799	16799	16799
R^2	-	-	0.191
Pseudo R^2	0.190	0.187	-
Firm Controls	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes

Table 1:14: NRSRO and Dodd-Frank

EJR rating levels before and after the NRSRO designation (Jan 2005 - Jul 2010) and EJR rating levels before and after Dodd-Frank (Dec 2007 - Dec 2014). Columns (1) and (2) show results for ordered logit models to capture the EJR rating level evolution after the EJR rating company got the NRSRO designation for firms defined as High-Fee. In columns (1) and (2) the sample period is restricted from January 2005 until July 2010 (when the Dodd-Frank Act was passed). NRSRO is a dummy that takes a value equal to 1 starting from December 2007, when EJR got the NRSRO designation, until July 2010. High-Fee is a dummy that takes a value equal to 1 if the average number of bonds issued by each firm in the sample, in every year-quarter, is above the average number of firms issued by the industry to which the firm belongs. Firm-specific controls, like firm size squared, market to book, profitability, debt issuance and leverage, are included. All the firm controls are lagged one period and interacted by the High-Fee dummy. Columns (3) and (4) show results for ordered logit models to capture the EJR rating level evolution after Dodd-Frank for firms defined as High-Fee. In columns (3) and (4) the sample period is restricted from December 2007 (when the NRSRO designation was assigned to EJR) until December 2014. Post Dodd Frank is a dummy that takes value equal to 1 starting from July 2010 until December 2014. In columns (1) - (4) industry fixed effects and a time trend are included. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Jan 2005 - Jul 2010		**Dec 2007 - Dec 2014**	
	(1)	(2)	(3)	(4)
	EJR	EJR	EJR	EJR
NRSRO	-0.595***	-0.629***		
	(0.105)	(0.114)		
(NRSRO)×(High-Fee)	0.297**	0.289**		
	(0.132)	(0.133)		
(High-Fee)	-2.012***	-2.012***	-0.215	-0.170
	(0.476)	(0.476)	(0.307)	(0.308)
Post Dodd-Frank			-0.0775	-0.210***
			(0.0713)	(0.0781)
(Post Dodd-Frank)×(High-Fee)			0.295***	0.283***
			(0.0944)	(0.0944)
$Size^2$	0.0424***	0.0422***	0.0469***	0.0463***
	(0.00275)	(0.00276)	(0.00192)	(0.00192)
$Size^2$×*(High-Fee)*	0.0110***	0.0110***	0.00399*	0.00397*
	(0.00344)	(0.00344)	(0.00227)	(0.00227)
N	3557	3557	7262	7262
Pseudo R^2	0.211	0.211	0.227	0.227
Firm Controls	Yes	Yes	Yes	Yes
Time Trend	No	Yes	No	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

CHAPTER 2.
RATING CHANGES AND CEO TURNOVER

Introduction

A large body of research has focused in recent years on the relation between firm performance and management turnover, finding that poor performance is an important determinant of executive turnover. However, even if important, firm performance is not the sole determinant of management turnaround. As stated by Brickley (2003),

> *"while the results are statistically significant, firm performance continues to explain very little of the variation in CEO turnover. We will have to consider other less explored issues to increase our understanding of CEO turnovers and replacements."*

This paper investigates the role of credit rating changes on CEO turnover. In light of the ongoing discussion about the role played by credit rating agencies in corporate scandals and in the recent crisis, understanding this relation is of particular interest. Generally speaking, our purpose is to investigate, both theoretically and empirically, the impact of credit rating changes on corporate governance decisions, and in particular the sensitivity of CEO turnover to credit rating changes. To this aim, we construct a theoretical model in which, within an adverse selection setting, shareholders can ex-post reduce informational asymmetries by relying on the report of a credit rating agency that collects a signal about the CEO talent, and thus of the firm's prospects. The information provided by the rating agency is imprecise, but positively correlated with the CEO true characteristics, and triggers a rating change. In particular, a high signal triggers an upgrade, while a low signal triggers a downgrade. The outcome realization, along with the rating change, is used to set the contract terms, namely the CEO's compensation and the probability of turnover. Within this setting, we show that one way for the good quality CEO to signal her talent is through weak entrenchment. In particular, an executive who is confident about her talent is more willing to accept a turnover in case of downgrade, because she knows that a bad rating is less likely than it would be if she were not so confident. This in turn implies that she is relatively less entrenched than low quality CEOs. We also find that such signalling role of a weak entrenchment becomes more valuable when the informativeness of the report of the rating agency decreases, the firm's level of investment increases and the rating fees decrease. In such circumstances the confident executive has to offer an increased turnover probability in case of downgrade to separate from the less confident one.

Our empirical test aims at understanding whether rating changes, and more specifically downgrades, have an effect on management turnover, and to which extent this effects depends on the degree of managerial entrenchment. This test is performed by exploiting CEO-level data and firm-level data. Following existing literature, we consult several online resources (Wall Street Journal, Bloomberg Business Journal, Company Websites, Washington Post, among others) and construct a CEO turnover database by classifying a turnover as forced if the news on CEO departure mentions pressures from the board of directors, forced resignation, scandal, reorganization, demotion, policy or personality disagreement and poor performance.

This database allows us to carry out several tests.

First, we are able to study whether a rating change, be it an upgrade or a downgrade, has an effect on the probability of CEO turnover. According to the theoretical model such a relationship exists, but it only holds for downgrades. This finding is confirmed by our empirical results showing that, while the positive signal coming from a rating upgrade does not affect the probability of management replacement, the negative signal carried by a rating downgrade has a significant impact on the firm's corporate governance.

Second, we try to dig more deeply into the relation between rating changes and turnover by distinguishing whether the replacement is *internal* or *external*. An internal replacement occurs when the new CEO is chosen inside the company. Conversely, an external turnover occurs when the new CEO is chosen outside the company, most likely within the same industry. We find that when, following a negative rating change, a management turnover occurs, the new CEO is more likely to be chosen from outside the company. The rationale behind this result is the following. A firm that puts a large weight on the downgrade will not only remove the existing CEO, but will also choose its substitute outside the company's management so as to send a strong signal of a change of gear.

Third, we want to test empirically the relation between managerial entrenchment and turnover. The theoretical model suggests that high-quality managers, who believe in their future performance, are more likely to accept contracts with a turnover as a way to signal their characteristics. Thus, they are less entrenched and the firms employing them display a higher profitability relative to firms with more entrenched CEOs. While this last finding has been corroborated by several studies (Malatesta and Walkling, 1988; Berger *et al.*, 1997, among others), the relation between the degree of entrenchment and the probability of turnover has not been explored so far in the literature. To test whether such a relation exists, we rely on a standard measure of managerial entrenchment based on the number of anti-takeover provisions. To this aim, we divide the sample into two subgroups to account for strongly-entrenched firms

(firms where the manager is highly "protected" via a large number of anti-takeover provisions) and weakly-entrenched firms (firms where the manager is weakly protected because of a low number of anti-takeover provisions). The results highlight that the link between ratings and turnover is weakened when managers are extremely tied to their role inside the firm. In other words, for a manager which is highly entrenched, it is less likely that a negative rating will translate into an increased probability of being dismissed from her job.

Fourth, we study the impact of the reliability of the credit rating on turnover probability. According to the theoretical model, when the information conveyed by the credit rating agency becomes more reliable, the probability of turnover following a downgrade increase. We test this prediction by focusing on the post-2007 crisis. During this period, credit rating agencies have experienced a reputational loss that has induced more timely and accurate ratings. As a consequence, in the post-crisis period, the information provided by credit rating agencies has become more reliable than the information released in the pre-crisis period (Cheng and Neamtiu, 2007). Given the superior information content of credit ratings, high quality managers have a reduced need to signal themselves through the threat of replacement. Following this intuition, we should observe a weaker relation between rating changes and management turnover in the recent post-crisis period. The results confirm this hypothesis. Moreover, they are robust to the inclusion of industry related variables and business-cycle related controls.

Lastly, we investigate the link between credit rating changes and management turnover within specific firms. Following the intuition suggested by the theoretical model, we study whether a CEO turnover following a rating change for firms that invest less than the industry median and for firms who pay relatively high rating fees, as proxied by the number of bonds outstanding. The empirical results show that, within these two groups of firms, the link that relates credit rating downgrades to management turnover is weakened.

The paper is organized as follows. Section 1 presents a brief review of the related literature. Section 2 outlines the theoretical model. Section 3 derives a comparative static analysis, followed by some empirical predictions in Section 4. Section 5 provides details about the data used and a full explanation of the variables construction. Section 6 presents the empirical results. Section 7 conducts an instrumental variable analysis to deal with the endogeneity problem. Section 8 concludes.

2.1 Related Literature

Management turnover is an important event in a firm's life with strong implications on the firm's investment and financing decisions. Denis and Sarin (1999) find that CEO turnover causes firms to be less diversified and smaller, with a subsequent increase in the cost of debt. On the other hand, Berger *et al.* (1997) demonstrate that CEO turnover is associated with substantial increases in leverage and stock performance improvements. Adam and Mansi (2009) analyze the impact of CEO turnover announcements on bondholders wealth, stockholders wealth and overall firm value, showing that CEO turnover events, although beneficial to stockholders, are value decreasing to bondholders and, in general, have an insignificant impact on firm value. However, management turnover is not an isolated episode of a firm's life, but is often triggered by events related to firm performance, M&A, or industry or market performance.

The existence of a negative relation between the likelihood of CEO turnover and firm performance is documented, for example, in several studies, which include Coughlan and Schmidt (1985), Warmer, Watts and Wruck (1988), Weisbach (1988), Gibbons and Murphy (1990), Murphy and Zimmerman (1993), Blackwell, Brickley and Weisbach (1994), Kang and Shivdasani (1995). A more recent paper, Jenter and Lewellen (2014), tries to go deeper in the study of the performance-turnover link examining two aspects: (1) the persistence of the effects of performance on manager turnover, and (2) the different impact of recent performance with respect to past performance. Their findings suggest that the effects of performance on turnover are as high in the first five tenure years as in the next five with a decline only after tenure year 10. Further, CEO departures in all tenure years respond strongly to recent performance but are almost insensitive to performance in the more distant past. Chakraborty et al. (2009) study, both theoretically and empirically, the relation between incentive compensation and (*performance related*) CEO turnover, finding that steeper incentives go together with higher likelihood of performance related termination. Thus, a poor performance associated to high-powered incentives signals a low quality, thereby triggering a turnover. Along a similar line, Chakraborty and Sheikh (2015) study the relation between option compensation and forced CEO turnover. Using a sample of 141 forced CEO turnovers between 1993 and 1999, they find that CEOs who receive higher option compensation are more likely to lose their jobs for poor performance. This effect is weakened for influential CEOs (i.e., those with long tenures and inside appointments) and for firms with poor governance structures.

The relation between firm performance and management turnover has been analyzed in various countries, as shown in Barucci, Bianchi and Frediani (2006) and Kato and Long (2006). Barucci, Bianchi and Frediani (2006) study CEO turnover in the Italian financial market for all listed companies during the sample period 1992-2003. The results show that CEO turnover is higher for poorly performing firms, unless the company is controlled by a family member, and that a weak internal governance, proxied by the board composition and the cash flow-voting rights wedge, is associated with a low turnover rate. Kato and Long (2006) get similar results for a sample of China's listed firms from 1998 to 2002. In particular, they find that CEO turnover is inversely related to firm profitability, but that this link is weaker for listed firms still controlled by the state.

But firm performance is only but one possible determinant of CEO turnover. If it is true that credit ratings are opinions about the firm probability of default and higher ratings are associated to better quality firms, it is also true that credit rating agencies often revise their evaluations without waiting for a change in firm performance to happen. As a result, in the last decade, many papers have attempted to explain the turnover event separately from the firm performance. One attempt is Lehn and Zhao (2006), who analyze the relation between M&A returns and subsequent CEO turnover for 714 firms that completed acquisitions from 1990 through 1998. They find an inverse relation between the value created by M&A activity and the probability of turnover, meaning that if the CEO completes an acquisition that creates shareholder value, then it is expected that she will be rewarded with extended tenure, for instance. Conversely, if the acquisition destroys shareholder value, then the CEO will face a higher probability of replacement. Firms that replace their CEOs after acquisition announcements face highly negative returns relative to firms that do not follow this strategy. Consistently with Lehn and Zhao (2006), Jenter and Kanaan (2014) investigate the factors affecting the management turnover out of the firm panorama. Using a hand-collected sample of 3,365 CEO turnovers from 1993 to 2009, they document that CEOs are significantly more likely to lose their job after bad industry performance and, to a lesser extent, after bad market performance. In particular, a decline in industry performance from the 90^{th} to the 10^{th} percentile doubles the probability of turnover.

In common with the literature that studies CEO turnover beyond firm performance, our paper investigates the role of ratings in CEOs' firing decisions. However, besides the relation with this literature, our paper is also related to various other strands of the literature.

At a theoretical level, the paper is related to the literature on signaling (Spence, 1973, 1974). Relative to this literature, in our paper it is the weak protection against managerial turnover that plays the role of signal. Indeed, since a good CEO is less likely to fail, she bears a lower cost from jeopardizing her job in case of failure than a bad one, thus making the degree of entrenchment an effective signaling device.

In focusing on the firm's firing decisions, the paper contributes to the literature on personnel economics. However, this literature has considered firing decisions as the result of some negative shock to a firm or its industry or the result of an individual proving to be significantly less productive, and has focused on the adverse consequences of such decisions on workers. Thus, like most corporate finance literature cited above, all this literature considers turnover as performance related and not as a response to a negative signal, as we do.

By studying the sensitivity of CEO turnover to credit rating changes, our paper contributes also to the growing literature relating credit ratings and corporate governance decisions. One example is provided by Alali *et al.* (2012), who show that improvements in corporate governance standards are positively correlated with improvements in credit ratings, with more pronounced effects among small companies. Kang and Liu (2009) show that rating changes have an effect on CEO equity-based compensation plans, with downgrades being more effective than upgrades. Their main findings suggest that CEO incentives, measured by pay-performance sensitivities, increase following rating downgrades and decrease following rating upgrades. However, monetary incentives are not the only dimension of incentives that we should consider. The threat of being dismissed should induce the CEO to exert a greater effort. Most important, how much CEOs are willing to take the risk of being replaced can be taken as evidence of the CEOs' confidence about future performance and, indirectly, of the CEOs' quality. Understanding the quality of the management in place becomes extremely important after negative rating changes which, undoubtfully, have a negative impact on firms' reputation.

Lastly, the paper is related to the literature studying the relation between entrenchment and firm value (the dynamics of managerial entrenchment). This literature has shown that managerial entrenchment has adverse effects on management behavior and incentives and might harm shareholders by weakening the disciplinary threat of removal, thereby increasing shirking, empire building and extraction of private benefits (Manne, 1965). In support of this view, there exists substantial evidence showing that firms with strong managerial entrenchment have lower leverage, lower firm value and significantly lower profitability relative to firms where managers are not entrenched (Malatesta and Walkling, 1988; Berger *et al.*, 1997; among others). Different measures can be used to capture entrenchment. Gompers et al. (2003) construct a governance index (G-index, henceforth), based on 24 governance provisions, to proxy for the level of shareholder rights. Bebchuk *et al.* (2009) construct an entrenchment index (E-index, henceforth) based on a subset of the measures in the G-index that matter the most when analyzing corporate governance. Both papers are based on Investor Responsibility Research Center (IRRC) data, focus mainly on anti-takeover measures, and find that firms with high shareholder rights (low entrenchment) are associated with superior performance (higher firm value, higher profits, higher sales growth) compared to firms with relatively many anti-takeover provisions (high entrenchment). Moreover, the stock returns of firms with strong shareholder rights outperforms those of firms with weak shareholder rights. A more extensive governance index is provided by Brown and Caylor (2006) using firm-level governance information obtained from Institutional Shareholder Services (ISS). Unlike the other two indices, this index has the advantage of including a broader set of components of corporate governance than takeover defenses, like progressive practices (e.g., term limits and mandatory retirement age for directors, board-approved CEO succession plans), and is significantly positively related to firm's valuation, as measured by Tobin's Q. Last, some papers (Chakraborty et al., 2009; Chakraborty and Sheikh, 2015) demonstrate that performance related CEO turnover is more likely for weakly entrenched CEOs with high-powered incentives. We take a step further with respect to the existing literature in describing whether managerial entrenchment plays any role in the relationship between rating changes and management turnover.

Our research is based on the idea that credit rating changes can provide a signal about the CEO quality in the labor market and affect her probability of being replaced. To the best of our knowledge, this is the first paper that studies the relation between ratings and management turnover and the strength of this relation across entrenched and not entrenched firms.

2.2 A model with adverse selection

In this section we set up a simple model with unobservable CEO's characteristics that explicitly incorporates rating change related turnover.

2.2.1 Model setup and assumptions

Firm shareholders employ a CEO to run a risky project costing I. The project yields y in case of success and 0 in case of failure. The CEO can be of two types. A good-type CEO has probability of success equal to p_G. A bad-type CEO has probability of success p_B. The NPV of the project if undertaken by a good-type CEO is $V^G \equiv p_G y - I > 0$, while if undertaken by a bad-type CEO is $V^B \equiv p_B y - I > 0$. Assume that $p_G > p_B$, so that $V^G > V^B$. The CEO has private information about her type. Assume that the probability of the CEO being a good or a bad type, respectively, be α and $1 - \alpha$, and is common knowledge. Let $m \equiv \alpha p_G + (1 - \alpha) p_B$

denote the CEO's prior probability of success.

Both the CEO and the shareholders are risk neutral and protected by limited liability.

Shareholders can reduce informational asymmetries by collecting information on the quality of the CEO. In particular, upon the good outcome realization, they can resort to a rating agency (RA, henceforth) to obtain an assessment about the firm value at a cost c. This information is imprecise, but positively correlated with the CEO type. In particular, conditional on the CEO being a good type, the RA gets a high signal about the firm value with probability r_H, while it gets a low signal with probability r_L, with $r_H > \frac{1}{2} > r_L$. Conditional on the CEO being a bad type, the rating agency gets a high signal about the firm value with probability q_H, while it gets a low signal with probability q_L, with $q_L > \frac{1}{2} > q_H$. A signal triggers a rating change. In particular, a high signal triggers an upgrade (U), while a low signal triggers a downgrade (D). The outcome realization, along with the rating change, can be used to set the contract terms, namely the CEO's wage and the probability of replacement. In particular, denote with K_U the probability that the CEO will be kept in the firm upon an upgrade, and with F_U the probability that the CEO will be fired still upon an upgrade. Similarly, denote with K_D the probability that the CEO will be kept in the firm, and with F_D the probability that the CEO will be fired, both upon a downgrade. Finally, denote with w_K the CEO compensation when she is kept in place and with w_F the CEO compensation upon being fired.

Within this setting, we show that a weak protection against managerial turnover can be used as a signaling device.

The sequence of events is as follows.

1. Nature chooses the CEO type $s \in \{G, B\}$, which only the CEO observes.

2. The outcome $Y \in \{0, y\}$ is realized and publicly observed.

3. Conditional on a favorable outcome ($Y = y$), a rating agency is hired to collect information $\sigma \in \{H, L\}$ about the CEO talent, and thus provide a rating $R \in \{U, D\}$, at a cost c.

4. Conditional on the rating, payoffs are distributed and replacement decisions are taken.

A general game tree is sketched in Figure 1.

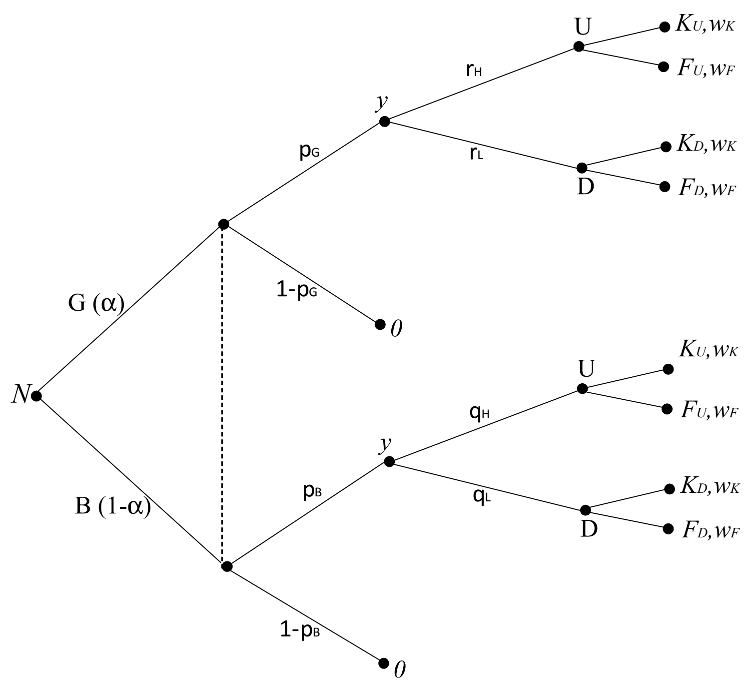

Fig. 1: The game tree

We first calculate the optimal contract under symmetric information when there is no rating agency. We next introduce asymmetric information and a role for the RA in screening types. Then, we show that the information provided by the RA and the threat of CEO turnover can be used to separate types. So, the threat of replacement is an extra disciplining device available to the shareholders.

2.2.2 Symmetric information

Under symmetric information, there is no need to resort to a rating agency. The contract sets type-contingent CEO compensations so as to

$$\max p_s w_s, \quad s \in \{G, B\}$$

subject to the shareholders getting non-negative returns: $p_s (y - w_s) \geq I$. Thus, $w_G = \frac{1}{p_G} (p_G y - I) = \frac{V^G}{p_G}$, and $w_B = \frac{1}{p_B} (p_B y - I) = \frac{V^B}{p_B}$, with $w_G > w_B$. Using w_s, $s \in \{G, B\}$, in the objective function, the good-type CEO gets V^G, and the bad-type V^B.

The symmetric information outcome however is not robust to asymmetric information. Indeed, since $w_G > w_B$, the bad-type CEO is willing to take the contract of the good-type CEO. This implies that the shareholders break even on the good-type but make losses on the bad-type. Anticipating this, the shareholders refuse to lend since they make losses in expected terms.

Let us then consider a contract that pools the two types of CEOs, in particular a contract that gives the CEO a compensation $w \geq 0$ in case of success and 0 in case of failure. The shareholders' profit for such a contract is therefore on average $m (y - w) \geq I$.

The CEO's compensation w is set so that shareholders break even across types.

Thus, $w^P = \frac{1}{m}(my - I)$, with expected return across types

$$V^P = my - I.$$

We last work out the good CEO expected return under a pooling contract. This allows us to work out how much the good type looses due to asymmetric information. Using w^P in the good CEO's expected return $p_G w$ gives:

$$V^{G\text{-}P} = V^G - \frac{(p_G - p_B)(1-\alpha)}{\alpha p_G + (1-\alpha) p_B} I, \tag{2.1}$$

where the last term expresses the loss to the good CEO due to asymmetric information, and thus the cross-subsidisation from the good to the bad type.

In what follows, we will show that it is possible to use weak entrenchment as a signaling device. In particular, since a good manager is less likely to fail, she bears a lower cost from jeopardizing her job in case of downgrade than a bad one. Thus, in order to separate from the bad type and signal her quality, she will then be willing to take contract terms which do not appeal to bad types (while allowing shareholders to break even).

2.2.3 Asymmetric information: Signalling through weak entrenchment

One way for the good-type CEO to convey information to investors is to accept a low protection against managerial turnover.

Suppose that, upon the good outcome realization, a rating agency is asked to provide a valuation about the firm. The valuation obtained is positively correlated with the true CEO's quality and triggers a rating change of the firm. In particular, if the firm is managed by a good quality CEO, a high valuation is obtained with probability $r_H > 1/2$, while a low valuation is obtained with probability $r_L < 1/2$. Similarly, if the firm is managed by a bad quality CEO, a high valuation is obtained with probability $q_H < 1/2$, while a low valuation is obtained with probability $q_L > 1/2$. A high valuation triggers an upgrade (U), while a low valuation triggers an downgrade (D). The outcome realization, along with the rating change, can then be used to set the contract terms. In particular, following an upgrade, a probability of being retained (fired) K_U ($F_U = 1 - K_U$) along with a repayment w_K (w_F) conditional on whether the CEO is retained (fired), is specified. Similarly, following a downgrade, a probability of being retained (fired) K_D ($F_D = 1 - K_D$) along with a repayment w_K (w_F) is specified.

We look for a separating equilibrium. The contract terms must then be set so as to allow the good CEO to credibly signal her type, namely, not appeal to a bad CEO and allow shareholders to break even when they know they face a good CEO.

Consider thus the problem faced by the good CEO of choosing a probability of retention (turnover) K_U, K_D (F_U, F_D) conditional on the rating (U, D), and a compensation $w_K(w_F)$ conditional on being retained (fired) upon the rating (K, F), that maximizes her expected payoff subject to the shareholders' breaking even on that CEO (i.e., when the corresponding probability of success is p_G), and to the good CEO's allocation not being preferred by the bad one to her symmetric information allocation (that is, to the constraint that the bad CEO obtains no rent over her symmetric information payoff) (and to the bad CEO not wanting to offer contractual terms $\{w_K, w_F, K_U, K_D\}$). A bad CEO, who in equilibrium is recognized by the shareholders, must obtain utility V^B : she cannot obtain more and she can guarantee herself V^B by demanding her full information reward w_B in case of success.

Thus, the shareholders take no risk in financing the CEO since at worst she is a bad type and they still break even. Thus, the maximization programme reads as follows (programme $\mathcal{P}^{RA}$):

$$\max_{w_K, w_F, K_U, K_D} p_G \left\{ r_H \left[K_U w_K + (1 - K_U) w_F \right] + r_L \left[K_D w_K + (1 - K_D) w_F \right] \right\} \tag{2.2}$$

$$\text{st } p_G (y - c) - p_G \left\{ r_H \left[K_U w_K + (1 - K_U) w_F \right] + r_L \left[K_D w_K + (1 - K_D) w_F \right] \right\} - I \geq 0 \tag{2.3}$$

$$V^B \geq p_B \left\{ q_H \left[K_U w_K + (1 - K_U) w_F \right] + q_L \left[K_D w_K + (1 - K_D) w_F \right] \right\} \tag{2.4}$$

where (2.2) is the good CEO's expected return, constraint (2.3) is the shareholders individual rationality condition, ensuring that they break even when recognizing a good CEO, constraint (2.4) is the no-mimicking condition, ensuring that the bad CEO does not want to mimic the good one, i.e., she prefers the first-best contract designed for her type to the contract terms designed for the good type.

To make the problem interesting and introduce a role for a rating agency, we introduce the following assumption.

The NPV of the project when managed by a good-type CEO is greater than the NPV of the project when managed by a bad-type CEO, even when considering the expected rating agency's fees c, i.e.,

$$\frac{V^G}{p_G} - c > \frac{V^B}{p_B}.$$

Moreover, we introduce the following technical assumption to ensure that the probability of being fired upon a downgrade is bounded in the $[0,1]$ interval.

$r_H \frac{V^B}{p_B} > q_H \left(\frac{V^G}{p_G} - c \right).$

The properties of the optimal contract are described in Proposition **??**.

Proposition 1 Under the assumptions of the model, the probability of being fired upon an upgrade is zero ($F_U^* = 0$), while it is strictly positive upon a downgrade and equal to:

$$F_D^* = \frac{\frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - \frac{1}{p_B}\left(p_B y - I\right)}{q_L \frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - r_L \frac{1}{p_B}\left(p_B y - I\right)} > 0. \tag{2.5}$$

Moreover, the compensation upon being fired is zero ($w_F^* = 0$), while the compensation upon being retained is:

$$w_K^* = \frac{1}{\rho}\left\{ q_L \frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - r_L \frac{1}{p_B}\left(p_B y - I\right) \right\} > 0, \tag{2.6}$$

The CEO returns are $p_G\left\{r_H + r_L K_D^*\right\} w_K^* = p_G y - I - p_G c = V^G - p_G c$, lower than the first-best returns V^G.

Proof. In the Appendix. ■

CEO turnover can be explained as a response to imperfect information. It may serve to reveal information about the quality of CEOs. Low quality CEOs can be identified because they are not willing to condition their job on the rating agency report. High-quality CEOs, instead, have a higher willingness to accept a replacement upon a low valuation because they know there is a lower probability that such a valuation will be received from the rating agency. Put differently, signalling can occur here because it is relatively more costly for a bad CEO to accept a weak protection against turnover than for a good one. Since $q_L > r_L$, it is more likely that a low valuation will arrive from the rating agency and that she will be fired upon a downgrade.

The above problem can be represented diagrammatically. To this aim, let us rewrite the optimization problem in terms of expected returns upon an upgrade, $E_U \equiv K_U w_K + (1 - K_U) w_F$, and expected return upon a downgrade, $E_D \equiv K_D w_K + (1 - K_D) w_F$ (programme $\mathcal{P}^E$):

$$\max_{E_U, E_D} p_G (r_H E_U + r_L E_D) \tag{2.7}$$

$$\text{st } \frac{V^G}{p_G} - c \geq r_H E_U + r_L E_D \tag{2.8}$$

$$\frac{V^B}{p_B} \geq q_H E_U + q_L E_D. \tag{2.9}$$

By taking the MRS between E_U and E_D, we see that the good CEO profit function (2.7) is a straight line with slope:

$$\frac{dE_D}{dE_U}|_G = -\frac{r_H}{r_L}. \tag{2.10}$$

From the no-mimicking condition (2.9), we see that the bad CEO profit function is linear and downward sloping with vertical intercept $\frac{p_B y - I}{p_B q_L} = \frac{V^B}{p_B q_L}$ and slope $\frac{dE_D}{dE_U}|_B = -\frac{q_H}{q_L}$.

Thus, given that $r_H > \frac{1}{2} > r_L$ and $q_H < \frac{1}{2} < q_L$, the good type CEO will exhibit a higher MRS (in absolute value) than the bad type CEO, i.e., in the E_D-E_U space the isoprofit functions of the good type CEO have higher absolute slopes than the bad type CEO ones at any given point (moreover the absolute slope of the good type CEO profit function is larger than one, while the absolute slope of the bad type CEO profit function is smaller than one). This means that the good borrower requires a lower increase in her income in case of failure for a given decrease in her income in case of success to keep her utility constant, compared with the bad CEO. Put differently, a high-type CEO is inclined to accept a higher decrease in her expected return after a low valuation (higher probability of replacement F_D, lower compensation w_K) for a given increase in the expected return after a high valuation (lower probability of replacement F_U, higher compensation w_K) than CEOs of type L.

From the individual rationality constraint (2.8), we see that the shareholder's profit function is linear and downward sloping with vertical intercept $\frac{1}{r_L}\left(\frac{V^G}{p_G} - c\right)$, and the same slope of the good CEO isoprofit function.

The above program can be represented in the following diagram:

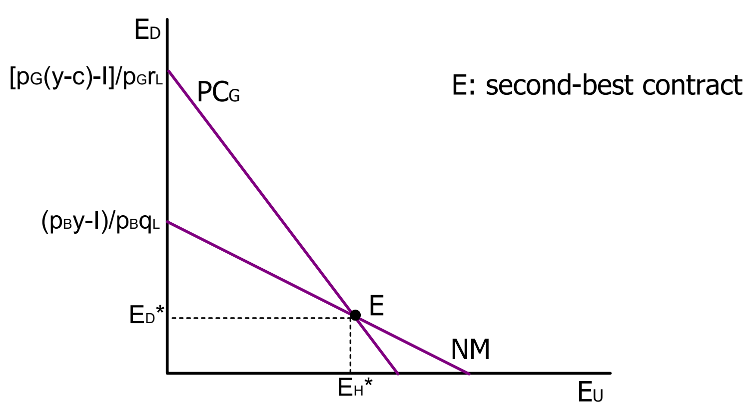

Fig. 2: The second-best contract

The good type CEO will then choose E_U and E_D that lies on the highest possible isoprofit function while satisfying the individual rationality constraint (2.8) and the no-mimicking condition (2.9). The solution of the programme is then obtained by taking the intersection of the two constraints and is given by:[1]

$$E_U^* = \frac{1}{\rho}\left[(q_L - r_L)\, y - q_L c + \frac{p_G r_L - p_B q_L}{p_G p_B} I\right], \tag{2.12}$$

$$E_D^* = \frac{1}{\rho}\left[(r_H - q_H)\, y + q_H c - \frac{p_G r_H - p_B q_H}{p_G p_B} I\right]. \tag{2.13}$$

where $\rho \equiv r_H q_L - r_L q_H > 0$ because of the positive correlation between signal and type. Notice that $E_U^* = w_K^*$ and $E_D^* = K_D^* w_K^*$.

2.2.4 Existence and uniqueness

The separating allocation is an equilibrium. To see why, consider that the good type offers two contracts. One specifying the probabilities of turnover conditional on the signal and the compensations conditional on whether turnover occurs, $\{F_U^*, F_D^*, w_K^*, w_F^*\}$, and one with no turnover specifying an uncontingent compensation, $\{0, 0, w_B, w_B\}$, which coincides with the first-best symmetric information contract. Once the shareholders agree to finance the project, they will break even what-

[1]Notice that for the problem to have a solution in the positive quadrant the vertical intercept of the individual rationality constraint must be higher than the vertical intercept of the no-mimicking constraint, i.e., $\frac{1}{r_L}\left(\frac{V^G}{p_G} - c\right) > \frac{1}{q_L}\frac{V^B}{p_B}$, which always holds.

ever the choice of each type of CEO, as the ex-post individual rationality constraints are satisfied (by construction of the contracts).

Indeed, the good CEO will choose $\{F_U^*, F_D^*, w_K^*, w_F^*\}$, as she gets a return higher than what she obtains by choosing the contract designed for the bad type (and this contract satisfies the individual rationality). The bad CEO will choose $\{0, 0, w_B, w_B\}$, as, by the no-mimicking constraint, she gets a return no less than the one she would obtain by choosing the contract designed for the good type.

In order to assess whether the separating allocation is unique, we have to check whether the contract with turnover is preferred by the good type to a pooling contract. To this aim, let us compare the cost of resorting to a rating agency with the cross-subsidisation involved in the pooling contract. From the expected return to a good quality CEO under a pooling contract $V^{G\text{-}P}$ (Eq. 2.1), we know that the cross-subsidisation from the good to the bad type is equal to $\frac{(p_G - p_B)(1-\alpha)}{\alpha p_G + (1-\alpha) p_B} I$. From Proposition 1, we have seen that the cost of resorting to a separating contract for a good type is instead $p_G c$. Comparing the two and solving for α, we find that it is optimal to use weak entrenchment as a signalling device if the shareholders' belief that the CEO is good is lower than some threshold, that is, if and only if

$$\alpha \leq \alpha^* \equiv \frac{p_B \left[p_G (y-c) - I\right] - p_G (p_B y - I)}{(p_G - p_B)(p_G c + I)}.$$

By Assumption 1, $\alpha^* > 0$, and, for $c > 0$, it is less than one.

2.3 Comparative static analysis

In order to derive some testable implications, we perform a comparative static analysis of turnover probability F_D^* and CEO compensation conditional on not being fired w_K with respect to investment over revenues I/y and rating fee c. Moreover, we investigate the role of the informativeness of the signal on the turnover decision.

To investigate the sensitivity of F_D^* to changes in capital expenditure, we express the probability of being fired upon a downgrade in terms of a new variable, capital expenditures over revenues (sales). Thus:

$$F_D^* = \frac{\frac{1}{p_G}\left[\left(p_G - \frac{c}{y}\right) - \frac{I}{y}\right] - \frac{1}{p_B}\left(p_B - \frac{I}{y}\right)}{q_L \frac{1}{p_G}\left[\left(p_G - \frac{c}{y}\right) - \frac{I}{y}\right] - r_L \frac{1}{p_B}\left(p_B - \frac{I}{y}\right)}$$

and by taking the derivative with respect to I/y

$$\frac{\partial F_D^*}{\partial\left(\frac{I}{y}\right)} = \frac{p_G p_B y\left(q_L r_H - q_H r_L\right)\left\{\left[p_G\left(y-c\right)-I\right]-\left(p_B y - I\right)\right\}}{\left\{r_L p_G\left(p_B y - I\right) - p_B q_L\left[\left(p_G\left(y-c\right)-I\right)\right]\right\}^2},$$

which is positive by Assumption 1. Moreover, the expected return upon a downgrade E_D^* (2.13) is decreasing in I/y :

$$\frac{\partial E_D^*}{\partial\left(\frac{I}{y}\right)} = -\frac{p_G r_H - p_B q_H}{p_B p_G\left(q_L r_H - q_H r_L\right)} < 0$$

while it is unclear the sign of $\partial E_U^* / \partial\left(\frac{I}{y}\right)$.[2]

The intuition behind this result is as follows. When investment over total sales increases, the firm has less resources to repay shareholders and satisfy the individual rationality constraint. Moreover, an increase in I/y makes the contract designed for the good type more attractive for the bad type (i.e., violates the no-mimicking condition). Thus, both the shareholders participation constraint and the no-mimicking

[2] From (**??**), this is equal to $\frac{\partial E_U^*}{\partial\left(\frac{I}{y}\right)} = \frac{p_G r_L - p_B q_L}{p_B p_G\left(q_L r_H - q_H r_L\right)}$.

condition shift downwards. To make up for this lack of resources and restore incentives, the confident CEO is willing to accept an lower protection against turnover in case of downgrade, and thus a lower expected return upon a downgrade.

As regards the rating fees, we find that the probability of being fired upon a downgrade decreases in c :

$$\frac{\partial F_D^*}{\partial c} = -\frac{p_B p_G^2 \left(q_L r_H - q_H r_L\right)\left(p_B y - I\right)}{\left[p_G r_L \left(p_B y - I\right) - p_B q_L \left(p_G \left(y - c\right) - I\right)\right]^2} < 0.$$

The expected return upon a downgrade E_D^*, instead, is increasing in c

$$\frac{\partial E_D^*}{\partial c} = \frac{q_H}{q_L r_H - q_H r_L} > 0.$$

Thus, as c increases, the expected return upon a downgrade increases, while the expected return upon an upgrade falls, $\frac{\partial E_U^*}{\partial c} = -\frac{q_L}{q_L r_H - q_H r_L} < 0.$

Although apparently counterintuitive, the results can be better understood through a diagrammatic analysis. In particular, from Fig. 2, we see that an increase in the rating fees affects only the individual rationality constraint, which shifts downwards along the no-mimicking condition (Fig. 3). Thus, starting from the initial optimum in point E, for given E_D, an increase in c in the participation constraint can be compensated by a reduction in E_U. However, such reduction makes the contract designed for the good type less attractive for the bad type (it slackens the no-mimicking condition). This mitigates the signaling role of turnover, making it possible to increase E_D through an increase in K_D (i.e., a reduction in the probability of turnover F_D), thus getting to point E'.

Last, we check how the probability of turnover upon a downgrade F_D^* varies

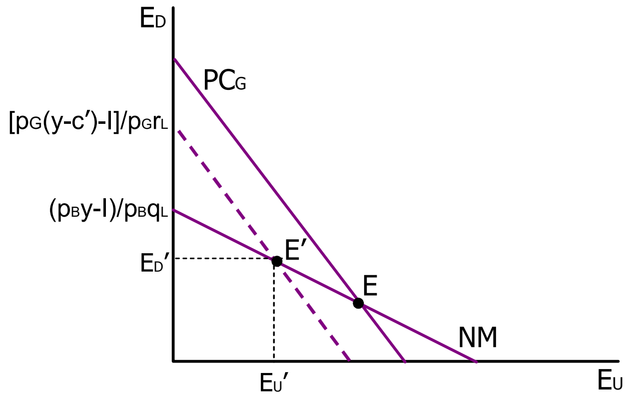

Figure 2..1: Fig. 3: The effect of a change in rating fees

with r_H and q_L. In particular, we have that:

$$\frac{\partial F_D^*}{\partial r_H} = \frac{p_G\left(p_B y - I\right)\left\{\frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - \frac{1}{p_B}\left(p_B y - I\right)\right\}}{\left\{\frac{1}{p_B} r_L\left(p_B y - I\right) - \frac{1}{p_G} q_L\left[p_G\left(y-c\right)-I\right]\right\}^2}$$

which is positive, given that the numerator is positive by Assumption 1. Similarly,

$$\frac{\partial F_D^*}{\partial q_L} = -\frac{\left[p_G\left(y-c\right)-I\right]\left\{r_H\frac{1}{p_B}\left(p_B y - I\right) - q_H\frac{1}{p_G}\left[p_G\left(y-c\right)-I\right]\right\}}{\left\{\frac{1}{p_B} r_L\left(p_B y - I\right) - \frac{1}{p_G} q_L\left[p_G\left(y-c\right)-I\right]\right\}^2} < 0$$

which is negative, given that the term in curly brackets in the numerator is positive under Assumption 2.

In graphical terms, we know that, as r_H and q_L increase, the participation constraint of the shareholders dealing with a good type rotate rightwards (clockwise), while the no-mimicking condition rotates inwards (counterclockwise). This implies that the intersection between the two functions shifts northwest, i.e., E_U decreases and E_D increases. To see this, let us take the derivative of E_U^* and E_D^* (2.12 and

2.13) with respect to r_H : [3]

$$\frac{\partial E_U^*}{\partial r_H} = \frac{\partial w_K}{\partial r_H} < 0,$$

$$\frac{dE_D^*}{dr_H} = q_H \frac{\frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - \frac{1}{p_B}\left(p_B y - I\right)}{\left(q_L - r_L\right)^2} > 0,$$

as argued through the graphical analysis.

Similarly, by taking the derivative of E_U^* and E_D^* with respect to q_L :

$$\frac{dE_U^*}{dq_L} = \frac{dw_K}{dq_L} < 0,$$

$$\frac{dE_D^*}{dq_L} = r_H \frac{\frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] - \frac{1}{p_B}\left(p_B y - I\right)}{\left(q_L - r_L\right)^2} > 0.$$

Under maximum informativeness of the signal, $r_H = q_L = 1$ and $r_L = q_H = 0$. Using this in (2.12) and (2.13), these become:

$$E_U^* = y - c - \frac{1}{p_G} I = \frac{1}{p_G}\left[p_G\left(y-c\right)-I\right] = \frac{V^G}{p_G} - c > 0$$

$$E_D^* = y - \frac{1}{p_B} I = \frac{1}{p_B}\left(p_B y - I\right) = \frac{V^B}{p_B} > 0,$$

$$K_D^* = \frac{p_G}{p_B}\frac{p_B y - I}{p_G\left(y-c\right)-I} = \frac{\frac{V^B}{p_B}}{\frac{V^G}{p_G} - c} < 1, \text{ whence, } F_D^* > 0.$$

Thus, under maximum informativeness of the signal, the individual rationality constraint becomes vertical and the no-mimicking condition horizontal, with E_U^* set at the lowest possible level, equal to $\left(V^G - p_G c\right)/p_G$, and E_D^* set at the highest possible level, equal to V^B/p_B. However, because $r_H = q_L = 1$ and $r_L = q_H = 0$, a good

[3]Recall that r_H expresses the probability with which, conditional on the CEO being a good type, the rating agency gets a high valuation about the firm value, while q_L expresses the probability with which, conditional on the CEO being a bad type, the rating agency gets a low valuation about the firm value. The more informative the signal, the closer to 1 will be such probabilities (and the closer to zero bill be r_L and q_H).

type is never misclassified, i.e., is never erroneously detected as bad. Thus, although $E_D^* = V^B/p_B > 0$ and $F_D^* > 0$, in equilibrium the good type is never fired (because the low signal is a zero probability event).

2.4 Empirical predictions

We have shown so far that CEO turnover can be explained as a response to imperfect information. In particular, the willingness to accept a replacement upon a downgrade works as a signal of the quality of the CEO. A high quality CEO has a higher willingness to accept to trade off an increased turnover probability in case of low signal with a high performance-based reward because she knows there is a lower probability that such a signal will be received by the rating agency.

Thus, better quality CEOs should display weak entrenchment and obtain higher compensations. As a consequence, we should observe that firm profitability is higher when managerial entrenchment is low. Moreover, we should also observe that both CEO turnover and compensations are higher when managerial entrenchment is low. So managerial entrenchment is negatively correlated with firm profitability and managerial turnover.

Existing theoretical literature so far (Shleifer and Vishny, 1989; Zwiebel, 1996; Novaes and Zingales, 1995; Benmelech, 2006; among others) has described entrenchment as actions that managers take, in the form of investment or capital structure decisions, to keep or secure their position, while hurting shareholders. In our theoretical model entrenchment is described as the limited willingness to accept a replacement that low quality managers have relative to high quality ones. In either case high entrenchment translates into low firm profitability and low firm value.

This leads to the following predictions.

Prediction 1 *Firms with weak managerial entrenchment display higher profitability relative to firms with strong managerial entrenchment.*

This has been proved in many empirical papers such as Malatesta and Walkling (1988) and Berger *et al.* (1997), among others. According to such papers, firms in which the management is strongly entrenched have lower leverage, lower value and significantly lower profitability relative to firms where the management is weakly entrenched.

Prediction 2. *Firms with strong managerial entrenchment display lower CEO turnover (relative to firms with weak managerial entrenchment).*

From the comparative static analysis of turnover probability, F_D, and CEO compensation conditional on not being fired, w_K, with respect to investment over sales, I/y, and rating fees c, we have derived the following predictions.

Prediction 3. *CEO's in firms with high capital expenditure over total sales show a higher turnover probability relative to CEO's in firms with lower capital expenditure over total sales (and thus lower managerial entrenchment).*

Thus, the higher the investment over total sales, the higher the CEO willingness to accept firing upon a downgrade. The intuition behind this result is the following. An increases in the level of investment over total sales (through either an increase in I or a decrease in y, or both), tightens both the participation and the no-mimicking constraints. As a consequence, to make up for the lower resources available to repay investors and still get financed, and to make sure that the bad CEO has no incentive to follow, confident CEOs must be willing to accept a lower expected return upon a downgrade, through an increased turnover probability in case of downgrade.

We have also looked at the effect on turnover probability of a change in rating fees, showing that the higher the rating fees, the lower the CEO willingness to accept firing upon a downgrade, i.e., the lower the probability of turnover upon a downgrade. To grasp the intuition behind this result, consider that when c increases, less resources are available to repay investors (the participation constraint becomes tighter). As a consequence, to make up for the lower resources available and still get financed, it is necessary to reduce E_U and, possibly, E_D, for example through a reduction in the CEO compensation w_K. However, such a reduction slackens the no-mimicking constraint, which was not affected by the initial increase in c. Thus, the contract designed for the good type becomes less attractive for the bad type. This implies that there is room to increase K_D, i.e., reduce the probability of turnover F_D upon a downgrade, thereby reducing the signaling role of turnover.

Prediction 4. *CEOs in firms with high rating fees are less likely to be fired upon a downgrade relative to CEOs in firms with low rating fees.*

We have also analyzed the effect of a change in the informativeness of the signal on turnover probability and compensation. We have shown that when the informativeness of the signal increases, the willingness to accept firing upon a downgrade falls. The intuition is as follows: The lower the informativeness of the signal, the less reliable the credit rating to signal the quality of the CEO. As a consequence, in order to credibly signal their quality, confident CEOs must be willing to accept an even lower protection against turnover in case of downgrade . This leads to the following prediction.

Prediction 5. *When the information conveyed by credit rating agency becomes less reliable, the probability of turnover following a downgrade increases.*

2.5 Sample Selection: Data Description

We use three databases in our analysis. Two of them are publicly available: the *Execucomp* database offers executive information and compensation data and the *Compustat* database provides financial and firm specific information. The third dataset is hand-collected and allows us to make a distinction between forced and voluntary turnovers.

The Execucomp database provides executive information on a yearly basis. In particular, it provides data about CEO personal characteristics, such as name, gender, age, nationality, and data about CEO compensation, such as total compensation, salary, bonus, equity and non-equity incentive plans. We construct a set of variables that may affect the probability of management turnover. More specifically, we define a variable, *CEO tenure*, denoting the length of the relation between the CEO and the company. The variable is constructed by taking the difference between the current year and the year in which the CEO first got her or his position in the firm. The correlation between CEO tenure and the probability of turnover can be either positive or negative. If positive, it is a signal that CEOs are close to retirement and their probability of being replaced increases. If negative, the length of the CEO relation becomes a signal of the firm's confidence towards the CEO. In addition, we define *CEO Age*, *Compensation*, and *Salary*. CEO compensation and CEO salary are constructed as the natural log of CEO total compensation and CEO total salary, respectively. We expect CEO compensation and salary to be negatively correlated to the probability of turnover, suggesting that CEOs that receive a higher reward are highly valuable to the firm and will less likely be replaced. The sign for CEO age is unpredictable. Weisbach (1988) and Murphy and Zimmerman (1993) find a positive correlation between CEO turnover and CEO age. However, CEO age could also be negatively correlated with the probability of CEO turnover supporting the idea that older CEOs are more experienced and, hence, have higher cost of turnover (the cost of replacement of these employees is generally higher). In addition, we control for the *CEO gender*. We construct a dummy variable equal to one if the CEO is a female.

The Execucomp database is merged with the Compustat database, which provides rating and firm characteristics.

We delete all the observations for which we do not have rating data. Following existing literature, we assign numerical values to S&P's ratings on notch basis: AAA=23, AA+=22, AA=21, AA-=20, A+=19, A=18, A-=17, BBB+=16, BBB=15, BBB-=14, BB+=13, BB=12, BB-=11, B+=10, B=9, B-=8, CCC+=7, CCC=6, CCC-=5, CC=4, C=3, D=2, SD=1. Ratings below 15 are defined as speculative ratings. Ratings above 15 are defined as investment ratings. Since most of the firm characteristics are available on a quarterly basis, we average the rating actions happening in the same quarter, meaning that if there is more than one rating action in the same year, we take the average of these ratings based on the above numerical conversion. Rating changes are defined as Upgrades or Downgrades. To define these rating changes, we construct a one period lag for each rating action and define the one period rating difference as the difference between the actual rating and the lagged one. Upgrades are defined by a dummy variable equal to one if the one period rating difference is positive (bigger than zero). Conversely, Downgrades are defined by a dummy variable equal to one if the one period rating difference is negative (lower than zero). If the one period rating difference is zero, then no rating change happens.

To control for firm specific information that may affect the probability of CEO turnover, we look at the Compustat Fundamental Annual database. For firm specific variables, we control for size, total leverage, market to book, profitability and tangibility. Firm size (*Size*), or the natural log of the book value of total assets, is used to capture economies of scale. Intuitively, we expect the variable Size to be positively correlated with the probability of CEO turnover, meaning that larger firms care more about their credibility and reputation and thus are more willing to change the CEO in place with a well-organized CEO recruitment process if this is necessary to protect their image. To get firm size, we drop observations if total assets are negative or missing. Firm total leverage (*Total Debt Leverage*), or the ratio of the book value of long-term debt to the book value of total assets, is used to control for differences in the capital structure. We expect leveraged firms to have lower CEO turnover due to lower resources available for the recruitment process. We delete observations if the long-term leverage is missing. Firm growth opportunities are captured by the firm market-to-book (*Market-to-Book*). This variable is constructed as the ratio of the market value of assets over the book value of assets, where the market value of assets is defined as the market value of equity (close price multiplied by common shares outstanding) minus the book value of equity (total assets minus total liabilities plus deferred taxes and investment tax credit) plus the book value of total assets. We delete observations if market-to-book is missing, equal or lower than zero. Finally, we construct *Profitability* and *Tangibility*. Profitability is constructed as the ratio of operating income before depreciation and total quarterly assets, while tangibility is expressed as property plant and equipment over quarterly total assets. We restrict our analysis to non-financial firms.

The rating database and the database containing firm characteristics are merged manually by using firm ticker and fiscal year.

The Execucomp database and the Compustat database provide CEOs specific information and firm specific characteristics. However, since they provide no information on the reason behind the turnover, we hand-collect data in order to make a distinction between forced and voluntary turnovers.

In particular, following Farrell and Whidbee (2002), we review the press release (Wall Street Journal, Bloomberg Business Journal, Company Websites, Washington Post, among others) and, in line with the definition in Parrino (1997), classify the turnover as forced when the departure mentions pressures from the board of directors, forced resignation, scandal, reorganization, demotion, policy or personality disagreement and poor performance. Conversely, we classify the turnover as voluntary if the CEO resigns voluntarily, for personal reasons or to undertake new business activities, or, if aged above 60, decides to retire. If the reason for CEO departure is reported as "retirement" but the CEO is below 60 and no additional information is provided, again we classify the turnover as forced.[4]

This hand-collected database allows us to access two types of information. First, we can construct the exact date in which the turnover event has occurred. This is important to establish a temporal relationship between rating change and managerial turnover. Second, we can make a distinction between internal and external turnover. A turnover is internal when the new CEO is chosen inside the company, usually between the Chief Financial Officer and the Chief Operating Officer. A turnover is external when the new CEO is chosen outside, usually from related industries. The distinction between internal and external turnover becomes important to analyze how "strong" is the effect of the downgrade on corporate governance. Intuitively, a firm that is looking outside for a new manager is trying to get the best candidate among those available.

The total number of forced turnovers we observe in our sample is equal to 130. Many of these turnovers take place after 2000. The number of voluntary turnovers is equal to 483 and is stable over time. The maximum number of turnovers (forced or voluntary) is three for every firm in our sample. More than half of the firms in the sample experience a voluntary turnover. About 15% of the firms experience a forced turnover.

The hand-collected database is merged to the Execucomp database and the Compustat database using firm ticker, year and quarter. The total number of firms

[4] For completeness of exposition, we must mention another definition of CEO turnover in the literature that does not classify it into categories, such as voluntary or forced, internal or external. It is applied in Mikkelson and Partch (1997) and DeFond and Park (1999) and is simply defined as a change in the identity of the individual who is holding the CEO office.

is 698 for a sample period that goes from 1998 to 2014. Summary statistics about firm specific variables and CEO specific variables are provided in Table 2.1.

[Insert Table 2.1]

As shown in Table 2.1, we consider large firms with an average rating of BBB- (14). In our sample, CEOs are on average over 56 years old and have worked for the same company for about 6 years.

Additional summary statistics are presented in Table 2.2. Here, firms are distinguished based on the degree of managerial entrenchment.

[Insert Table 2.2]

Table 2.2 suggests that firms in which CEOs have a low degree of managerial entrenchment are larger, more profitable and with better growth opportunities than firms in which CEOs have a high degree of managerial entrenchment. In these firms, CEOs receive a larger compensation.

The next section will provide a more detailed description of the estimation technique used to test the relation between credit rating changes and CEO turnover.

2.6 Estimation

2.6.1 Logit Models

The relation between probability of turnover and rating changes is investigated using logit models. The first specification studies the link between the CEO probability of replacement, upgrades and downgrades. More specifically, we estimate the following model:

$$Prob(Turnover)_{cit} = \alpha_{it} + \beta_1 * Upgrades_{it-1} + \beta_2 * Downgrades_{it-1} +$$
$$+X'_{ct-1}\gamma_1 + W'_{it-1}\gamma_2 + \theta_{SIC} + \theta_t + \varepsilon_{cit}. \tag{2.14}$$

where the dependent variable is the probability of turnover for CEO c employed at firm i at time t. The CEO turnover is defined as a dummy variable that takes value one if a turnover has occurred relative to the previous year and it is classified as *forced*. X_{ct} is a vector of CEO characteristics (age, compensation, salary, tenure, gender). W_{it} includes firm specific controls (Size, Leverage, Profitability, Market to Book, Tangibility). The model is estimated using year-quarter fixed effects and industry fixed effects. Table 2.3 shows the results.

[Insert Table 2.3]

Column (1) analyzes the relation between CEO turnover and rating changes when no controls are taken into account. Column (2) considers the combined effect of time fixed effects and industry fixed effects. Columns (3) and (4) estimate the relationship by adding firm and CEO characteristics with and without industry fixed effects, respectively. Results indicate that, following a downgrade, the probability of CEO turnover increases. Upgrades have a negative effect on the probability of CEO turnover. However, this effect is not significant. The result is robust to the inclusion of firm and CEO specific controls. Profitable firms with higher rating levels will experience a lower probability of forced turnover.

2.6.1.a Internal versus External Turnover

Table 2.3 investigates the link between rating changes and management turnover without making a distinction between whether the new CEO is chosen within the same firm that has been downgraded. To further investigate the power of the rating signal in the turnover decision we distinguish between internal and external turnovers.

Internal turnovers are identified by a dummy variable that takes value one if the new CEO is chosen within the same firm that has received the downgrade. We construct external turnovers in a similar way, i.e., by a dummy variable that takes value one if the new CEO is chosen outside the firm that has been downgraded.

The logit models we estimate when we separately consider internal and external turnovers are given by:

$$\begin{aligned} Prob(Internal)_{cit} = {} & \alpha_{it} + \beta_1 {*} Upgrades_{it-1} + \beta_2 {*} Downgrades_{it-1} + \\ & + X'_{ct-1}\gamma_1 + W'_{it-1}\gamma_2 + \theta_{SIC} + \theta_t + \varepsilon_{cit} \end{aligned} \tag{2.15}$$

$$\begin{aligned} Prob(External)_{cit} = {} & \alpha_{it} + \beta_1 {*} Upgrades_{it-1} + \beta_2 {*} Downgrades_{it-1} + \\ & + X'_{ct-1}\gamma_1 + W'_{it-1}\gamma_2 + \theta_{SIC} + \theta_t + \varepsilon_{cit} \end{aligned} \tag{2.16}$$

Results are presented in Table 2.3 (Columns 5 and 6). The coefficient β_1 for upgrades is always negative but not statistically significant. The result for β_2 in Column 5 suggests that if a downgrade occurs, the CEO in place is more likely to be replaced with an outsider. The effect of downgrades on internal turnover is weaker and disappears when industry fixed effects are taken into account. All the controls have the expected sign.

The results are confirmed if we divide the sample between small rating changes (downgrades of at most one notch) and large rating changes (downgrades of two or more notches). We find that forced external turnovers occur following large rating changes (significant at 10% level), while small rating changes do not seem to have a significant impact on turnovers.[5] Last, internal turnover is not affected by either large or small rating changes.

2.6.2 Downgrades, Turnover and Entrenchment

In the theoretical model, we have shown that the degree of managerial entrenchment works as a signalling device: Under asymmetric information about CEO characteristics, a good quality CEO is less likely to have a low outcome and is more willing to accept to be replaced upon a downgrade. Thus, she displays a higher probability of turnover upon a downgrade and a lower degree of entrenchment relative to a low quality CEO.

[5] The reduced level of significance may be due to the large drop in the number of observations when considering large rating changes. It is nonetheless remarkable that the results, that are highly significant when considering the entire sample, become not significant when focusing on small rating changes. It is then likely that the results for the full sample are mainly driven by the large rating changes.

At an empirical level, we have seen that downgrades affect the firm's decision to dismiss the current manager. To test whether the degree of entrenchment weakens the relation between downgrades and CEO turnover, as predicted by the theoretical model, we should then observe that in firms with highly entrenched managers the power of a downgrade is lower than it is in firms with less entrenched CEOs and, hence, the threat of removal is not so strong for CEOs in those firms. To this aim, we identify the impact that a downgrade has on turnover across firms with entrenched and non-entrenched CEOs.

To capture CEO entrenchment, we use two measures widespreadly used in the literature. The first measure comes from Gompers, Ishii and Metrick (2003). Their entrenchment index (G-index) is broad and based on 24 governance provisions that the authors show to be negatively correlated with firm value as measured by Tobin's Q and stockholder returns during the 1990 decade. Data on these provisions are taken from the *Institutional Shareholder Service* (*ISS*, formerly RiskMetrics). We are able to get governance provisions on 536 firms from 1998 to 2006. The G-index is constructed as the sum, in a given year and for every specific firm, of all the available provisions. A deeper look at the data shows that more than half of the firms have an average number of corporate provisions between 8 and 11. Only about 3% of the firms have more than 15 provisions. An analysis of the number of provisions by year shows that the G-index is relatively stable with a number of provisions equal to 9 for every year we observe in our sample.

The second measure is proposed by Bebchuk, Cohen and Ferrell (2008). They construct an entrenchment index (E-index) focusing on six governance provisions, which they reckon to be the ones that matter the most when analyzing the corporate governance structure. Four of them - classified boards, limits to shareholder amendments of the bylaws, supermajority requirements for mergers and supermajority requirements for charter amendments - limit the extent to which a majority of shareholders can impose its will on management. Two other provisions are salient measures taken to oppose hostile offers: poison pills and golden parachute arrangements. Our E-index is constructed with data taken from the *Institutional Shareholder Service* (*ISS*, formerly RiskMetrics) and is defined as the sum of the above six provisions in every year-firm combination. Almost 70% of the firms in our sample have two or three of the provisions listed in the E-index (on average). Less than 1% of the firms have five provisions. None of the firms has all the six provisions. As the G-index, also the E-index is stable over time. The average number of provisions is about three.

We divide our sample into two distinct subsamples to distinguish between entrenched and unentrenched firms. Firms that are entrenched have a median number of provisions higher than the sample median. We distinguish entrenched firms from unentrenched ones by using either the G-index or the E-index.

Table 2.4, Panel A, shows results when firms are classified as *Strongly Entrenched* or *Weakly Entrenched* using the E-index.

[Insert Table 2.4]

The relation between forced turnover and downgrades is tested using different specifications. Columns (1) and (3) include year-quarter fixed effects and industry fixed effects, but not firm and CEO specific controls. Columns (2) and (4) add firm and CEO specific controls. The first two columns account for a high degree of managerial entrenchment. The last two columns, instead, for a low degree of managerial entrenchment. The results show that the effect of downgrades over forced turnover is weakened when managerial entrenchment is considered. Indeed, the coefficient for downgrades is not statistically significant in the first two columns, which suggests that the incentive power of downgrades is insufficient to trigger a turnover when CEOs are strongly protected by governance provisions (i.e., highly entrenched). The result is not affected by the specification used and all the controls have the predicted sign.

Table 2.4, Panel B, confirms the previous results using the G-index. As before, testing for different specifications, the main result highlights that the disciplining power of downgrades vanishes when highly protected CEOs are taken into account.

One last remark is in order here. Testing for the effects of managerial entrenchment allows us to weaken the endogeneity concerns that might arise when studying the relation between rating downgrades and management turnover. Indeed, we currently find that negative rating changes trigger CEO turnover. However, one might argue that the relation between rating changes and management turnover is endogenous: CEO removal and rating downgrades are events that are likely to happen in poor-performing firms. Those firms are more exposed to rating downgrades and, at the same time, more inclined to replace their CEO. This concern is nevertheless mitigated when we separate out the sample and analyze separately the relation between downgrade and turnover across entrenched and unentrenched firms. Indeed, following the standard literature on managerial entrenchment (Malatesta and Walkling, 1988;

Berger *et al.*, 1997), firms characterized by weak managerial entrenchment are overall more profitable than firms in which managers are highly tied to their position and, as a consequence, should be less exposed to CEO turnover, not more. Instead, in line with the predictions of our theoretical model, we find that the relation between rating changes and management turnover is stronger for firms with less entrenched CEOs.

2.6.2.a Probit Model with Selection: Rating Changes, Turnover and Entrenchment

The theoretical model suggests that more talented CEOs will signal their quality by accepting contracts that allow for a managerial turnover following credit rating downgrades. More talented CEOs are thus less entrenched and more exposed to turnover. As shown in the previous section, this theoretical prediction can be empirically tested by considering firms where managers are highly entrenched and firms where managers display a low degree of entrenchment. Another possibility to test this result is to use a probit model with selection (*Heckman model*). The probit model is a two-step model. In this specific setting, the first stage elaborates a model for the probability of being unentrenched, while the second estimates the relation between the probability of turnover and rating change by selecting firms where the CEO is less entrenched.

The specification for the first stage model is as follows:

$$Prob(Unentrenched)_{cit} = \alpha + \beta_1 Size + \beta_2 Leverage + \beta_3 Profitability +$$

$$+ \beta_4 CEOTenure + \beta_5 Salary + \beta_6 CEOAge + \theta_{SIC} + \theta_t + \varepsilon_{cit} \qquad ()$$

Unentrenched is a dummy variable that takes value one if, consistently with the discussion in the previous paragraph, the CEO is not entrenched and is not protected by anti-takeover provisions. We assume that the probability of being unentrenched depends on firm size, its level of leverage and profitability, as well as some CEO characteristics like tenure, salary and age. Year and industry fixed effects are included.

The second stage of the Heckman model describes the relation between the probability of managerial turnover and rating changes controlling for firm and CEO specific characteristics (as specified in Model 8). More intuitively, the adoption of the probit selection model allows us to study the probability of managerial replacement following credit rating changes by selecting firms where the CEO is less entrenched (i.e., firms with a lower number of anti-takeover provisions). Results for the Heckman model are provided in Table 2.5**.**

[Insert Table 2.5]

Part 1 illustrates the results for a probit selection model where the probability of CEO turnover following a rating change is estimated without including control variables. The first column shows results for the first stage estimation. The coefficients suggest that managers are less likely to be entrenched in large and profitable firms. In addition, managers that receive a higher salary are less likely to be entrenched.

Forced shows results for the second stage estimation. As expected, downgrades trigger a higher CEO turnover. Credit rating upgrades lower the probability of CEO replacement. However, the coefficient for upgrades is not statistically significant. Similar results obtain when we consider Part 2, where we augment the second stage regression with control variables. As before, the sign of the coefficients for the first stage regression are as expected. Moreover, downgrades affect CEO turnover while there is no effect from rating upgrades.

2.6.3 High-investment and low-investment firms

Prediction (3) states that, in firms with a high level of capital expenditure over total sales, managerial turnover following a downgrade is more likely than in firms with a low level of capital expenditure over sales. Intuitively, the reason why firms with a high level of investment should be more likely to experience a CEO turnover has to do with the fewer resources available to repay investors. As a consequence, to make up for the shortage of resources and still get financed, confident CEOs must be willing to accept a lower expected return upon a downgrade, through an increased turnover probability in case of downgrade.

To test this prediction we consider a subset of firms that are characterized by a high level of investment. We compute investment as the ratio of quarterly capital expenditures over quarterly total sales. We divide firms into two groups: those with high-investment and those with low-investment. High-investment firms are firms with a median investment above the industry median.[6] Low-investment

[6] Our benchmark for the investment analysis is the industry sector. It might happen that firms in specific industry sectors have higher levels of investment. In our sample, investment tends to be

firms are firms whose median investment is below the industry median. Results are provided in Table 2.6.

[Insert Table 2.6]

The first two columns refer to low-investment firms. The last two columns refer to high-investment firms. The results illustrate that in firms characterized by a high-level of investment, CEO turnover is more likely after a downgrade. The results are not affected by the specification used. All the controls have the predicted sign.

2.6.4 High-fee and low-fee firms

Prediction (4) states that, in firms with high rating fees, the probability of being replaced following a rating downgrade is lower than in firms with low rating fees.

To test this prediction, we need to measure the rating fees paid by the firm. Since they are unobservable, we proxy them by considering the firm's bonds issuance. Firms with a large bond issuance, having to resort more often to RAs, have to pay large rating fees. This may affect the managerial turnover phenomenon through various possible channels.

First (substitution effect), firms face a trade-off between various costly decisions. Those with new investment opportunities may issue bonds to finance them. The larger the amount of bonds issued, the more often the firms have to ask for rating

higher for sectors such as Semiconductors, Multi-Utilities, Electric utilities, Oil & Gas Exploration & Production, Oil & Gas Equipment & Services, Pharmaceuticals, Independent Power Producers & Energy Traders.

evaluations, the larger the fees they have to pay relative to firms issuing a limited amount of bonds. These firms might then try to limit other costly decisions, like a CEO turnover that imposes firing costs for the old CEO, as well as hiring and training costs for the replacement. If for the firm issuing bonds is necessary to carry out its investment projects, then the costly decision of replacing the CEO, even if needed, might be postponed, more so for firms with larger rating fees. In other terms, we expect the relation between rating downgrades and CEO turnover to be weaker for firms with larger bonds issuance, and thus higher rating fees.

Second (conflict of interests), credit rating agencies working for firms with large bonds issuance are more exposed to conflicts of interest.[7] Such firms have a close relationship with the rating agency, are more likely to pay larger fees and, consequently, can be thought of as being "good customers" in the eyes of credit rating agencies. The latter may thus have an incentive to inflate corporate ratings in the hope to stop issuers from resorting to alternative rating agencies. The rating fee paid is thus also a proxy for potential conflicts of interest between rating agencies and issuers. Given that conflicts of interest are more likely to arise when considering firms with a large issuance of bonds, we expect upgrades to be more likely than downgrades (i.e., rating inflation more likely) and, consequently, CEO turnover to be less likely if it is mainly triggered by negative rating changes. As before, we expect to see a weaker relation between rating downgrades and turnover for firms that face larger rating fees (as proxied by the number of bonds issued).

[7] The idea of using the number of bonds issued by every firm as a proxy for potential conflicts of interest for credit rating agencies is standard in the literature. Examples are provided in Covitz and Harrison (2003), Jiang et al. (2011) and Kraft (2011).

In order to identify firms that issue a large number of bonds, we construct a dummy variable, *High-Fee*, which takes value one if the median number of bonds issued by the single firm is greater than the median number of bonds over the entire sample.[8] Then, we estimate the relation between turnover and rating downgrades by considering the two sub-samples, the *High-Fee* firms and the *Low-Fee* firms. Results are presented in Table 2.7.

[Insert Table 2.7]

Table 2.7 is divided into four columns. Columns (1) and (2) focus on High-Fee firms. Columns (3) and (4) consider Low-Fee firms. Columns (2) and (4) add firm controls. Industry and year fixed effects are included. Standard errors are clustered at the firm level.

Results are consistent with our prediction. Columns (3) and (4) suggest that firms that issue a small amount of bonds are also the ones that are more likely to experience a CEO turnover following a rating downgrade. Conversely, firms that issue a large amount of bonds are less exposed to managerial turnover after downgrades. The results are robust to the inclusion of firm controls.

2.6.5 Pre- and Post-2007 Financial Crisis

The theoretical model suggests that when the information conveyed by credit rating agencies becomes more reliable, the probability of turnover following a downgrade decreases.

[8]In our sample, we have information about bond issuance on 434 firms. Among these, 294 can be classified as low-fee and 140 as high-fee.

One way to test this result is to consider how the relation between rating changes and CEO turnover evolves after the 2007 financial crisis. The choice of this period is justified by the reputational concerns experienced by credit rating agencies after 2007. Following the crisis, their activity has been more closely scrutinized, inducing more timely, accurate and informative ratings. Given the higher information content provided by ratings, we should expect the relation between rating changes and management turnover to weaken in the post crisis period. The intuition is the following. If it is true that accepting a contract with higher management turnover is a device that high-quality managers use to signal their ability and separate out from the low-quality ones, then the need to signal themselves through weak entrenchment should be lower when ratings are more reliable.

The approach we follow is to estimate model (2.14) in the pre-crisis period and in the post-crisis period. According to the NBER dates, the 2007 financial crisis has a stopping point in June 2009. Consequently, we define a dummy for the post-crisis period that takes value one starting from the third quarter of 2009.

One possible concern that might arise when estimating model (2.14) in the post-crisis period is that the results might be driven by *business cycle dynamics*. The post-crisis period is also the period of the firm recovery. This implies that when testing the relation between rating changes and turnover we need to account for the possibility that the number of CEO turnovers is decreasing because of an improved firm quality. To account for business cycle implications, we augment model (2.14) by including the log of GDP, past one-year market returns (using S&P 500 index), S&P 500 index level, perceived firm profitability,[9] the quarterly firm's stock market performance and the industry asset turnover.[10]

Results are presented in Table 2.8.

[Insert Table 2.8]

We test the effect of rating changes on CEO turnover by including year-quarter fixed effects and industry fixed effects. The table includes results when firm-specific controls and CEO-specific controls are considered. The results highlight that the relation between rating changes and CEO turnover is weakened in the post-crisis, suggesting that in this period reputational concerns for RAs have reduced the need for competent CEOs to rely on weak entrenchment to signal their quality.

2.7 Instrumental Variable Analysis

The tests performed in the previous pages are logit regressions of the CEO probability of turnover against lagged dummy variables for rating downgrades and upgrades. Despite lagging variables, endogeneity concerns might arise when studying the relation between rating changes and management turnover. One issue with this analysis is that poor performing firms may drive both the downgrade action and the CEO turnover. Indeed, poor performing firms are more likely to default and,

[9] To constuct the perceived firm profitability, we use the Institutional Brokers' Estimate System (IBES) Database. This variable is constructed as the analysts' forecasted earnings per share for the next fiscal year divided by the current share price.

[10] To construct business cycle variables, we need to merge the original dataset, including rating data and firm characteristics, with a dataset containing data on market returns and levels for S&P 500 firms, GDP quarterly data and equity analysts' forecasts.

consequently, more exposed to rating downgrades. In addition, as a response to the poor performance, these firms are more likely to replace their CEO. There exists, thus, a problem of omitted variables (i.e., firm profitability) that we need to address[11]. Since our concern is that the results might be driven by omitted variables, we conduct an instrumental variable analysis. To this aim, we need to find an instrument for rating downgrades that is "relevant" and "exogenous." In other words, we need to find an instrument that is correlated with the variable we think is endogenous (i.e., rating downgrades), but not directly related to our dependent variable (i.e. CEO turnover). We use a joint instrument.

The first instrument is *Analyst Coverage*, defined as the number of equity analysts covering a specific firm. As suggested by Fong et al. (2014), the presence of a large number of security analysts discipline credit rating agencies. This is because they mitigate the asymmetric information problem faced by that firm and, consequently, the optimism-bias in credit ratings. Firms covered by a large number of equity analysts are thus less likely to receive inflated ratings from credit rating agencies and, because of the greater monitoring exerted by equity analysts, more likely to receive downgrades. Following this argument, *Analyst Coverage* is likely to be correlated with the credit rating downgrade variable. However, there is no reason to believe that the number of equity analyst directly affects the probability of CEO replacement.

[11]Several factors may drive the relationship between rating downgrades and CEO turnover. News about restructuring plans (such as takeovers, M&A and firm split up) may, for instance, have an affect on both the probability of rating downgrades and CEO replacement. As shown in Healy, Palupu and Rubak (1990), significant economic improvements are expected after restructuring plans like mergers. Following this logic, rating downgrades are less likely to happen. However, these events are also likely to positively affect the probability of CEO turnover.

The second instrument we use is the *Equity Analyst Bias* (i.e., equity analyst pessimism/optimism). Credit ratings incorporate equity analyst forecasts and, thus, equity analyst recommendations. Consequently, as suggested by Fracassi *et al.* (2014), equity analysts pessimism/optimism, as reflected in equity analyst recommendations and equity analyst forecasts, affect credit ratings and corporate policies. A firm that is covered by more pessimistic equity analysts is more likely to receive lower equity recommendations that might trigger lower credit ratings. Firms that are covered by more pessimistic equity analysts are, thus, more exposed to credit rating downgrades. However, equity analyst bias is unlikely to be related to the firm probability of replacing the manager.

The first stage of the instrumental variable analysis is described as follows:

$$CRA\ Downgrade = \alpha + \beta_1 Analyst\ Bias + \beta_2 Analyst\ Coverage + \gamma_1 X_{t-1} + \theta_{SIC} + \theta_t + \varepsilon_{it}.$$

The variable we suppose is endogenous, the credit rating downgrade, is regressed against the two instruments, *Analyst Bias* and *Analyst Coverage* and some firm characteristics. *Analyst Bias* is a dummy variable that takes value one if in every year and quarter the firm is covered mostly by pessimistic equity analysts, that is, by equity analysts whose recommendation is below the average recommendation. *Analyst Coverage* is defined as the number of equity analysts covering a firm in every year/quarter. Industry fixed effects and year fixed effects are considered.

Results from the first stage regression are presented in Columns (1) and (2) of Table (2.9).

[Insert Table 2.9]

Results show that credit rating downgrades are affected by *Analyst Bias* and *Analyst Coverage*. Following the intuition provided above, firms covered by a large number of equity analysts are more likely to experience rating downgrades. Similarly, firms mostly covered by pessimistic equity analysts are more likely to receive rating downgrades. All the controls have the expected sign. The first stage allows to have an F-test for the *relevance* of the instruments. The rule of thumb establishes that instruments are not weak if the first stage F-statistic (H_0: coefficients of all instruments =0) is greater than 10. In our case, the first stage F-statistic is equal to 16.16 when we include year and industry fixed effects, which implies that our instruments are relevant and not weak.

Results from the second stage regression are presented in Columns (3) and (4) of Table (2.9). The results illustrate that, once instrumented for *Analyst Bias* and *Analyst Coverage*, credit rating downgrades significantly affect the probability of replacing the CEO. Since Columns (3) and (4) are obtained from a linear probability model, the coefficients reported in Table (2.9) can be interpreted as marginal effects of rating downgrades on the probability of CEO turnover. As shown in Column (3) (or Column (4)), following a rating downgrade, a forced CEO turnover is 18.5% likely to happen. The magnitude of the coefficient estimates are particularly large. The correlation between rating downgrades and management turnover caused by the omitted variable is the main driving force that biases the coefficient estimates of management turnover. Once we use the instrument to clean up the correlation between rating changes and the residuals (the firm's unobservable characteristics), the endogeneity of rating downgrades is removed and the coefficient estimates decrease, i.e., become more negative.

2.8 Concluding remarks

We study the relation between CEO turnover and credit rating changes. Using a simple adverse selection model that explicitly incorporates rating change related turnover, our model predicts that a negative credit rating change triggers turnover, more so the lower the managerial entrenchment and the less informative the report provided by the credit rating agency. Our empirical results confirm these predictions. We show that downgrades explain forced turnover risk and, more in detail, they are responsible for forced turnovers with the new CEO chosen outside the firm that has received the negative credit rating change. In addition, we find that the relation between rating changes and management turnover is stronger when the degree of managerial entrenchment is low. Finally, we show that the relation weakens for firms that issue a large number of bonds, for firms that invest less and in the post-2007 global financial crisis, when the reputational concerns for rating agencies are increased. In addition, results are robust to an instrumental variable analysis. The need to use an instrumental variable analysis is justified by the suspect of endogeneity of the relation between rating changes and CEO turnover: rating downgrades and forced CEO turnovers are events that are likely to happen contemporaneously for poor-performing firms. An instrumental variable analysis is thus needed to account for omitted variables related to firm profitability.

Our paper offers the opportunity to think about credit ratings from a different perspective.

Credit ratings are a valuable source of information to the bond and stock markets. Ratings provide information about firm's reputation and, as such, affect the firm ability to get financing and invest. However, ratings are also informative to the shareholders themselves. If a negative rating change is received, shareholders may try to restore their image by replacing the CEO in place. This is true independently of the information content carried on by ratings. Even in the scenario in which ratings are changing for reasons unrelated to firm performance, firms still respond to negative rating signals by changing their CEO. Firms are thus highly affected by ratings. Rating changes trigger real effects, in the form of changes in leverage and investment, but are also able to trigger changes in the corporate governance, in the form of a higher probability of CEO replacement.

Our analysis has left some issues open. In particular, in our theoretical model the degree of protection against managerial turnover is only but one aspect of the CEO contract. Another aspect is the CEO compensation. Clearly, in the model, a higher managerial turnover is accompanied by higher levels of pay to compensate managers for the greater risk in their compensation. This is in line with Hermalin (2005), who finds that the lower job stability induced by an increased monitoring intensity of CEOs goes together with an increased level of CEO pay. This view is broadly consistent with some empirical evidence, but there is no direct evidence that changes in governance has been the determinant of the rapid rise in CEO pay of the last 30 years (Frydman and Jenter, 2010). Although this aspect has not been analyzed in our work, the theoretical analysis may be further developed to deliver predictions on the role of monitoring on CEO compensation. We leave the development of this line of analysis and the empirical verification of the predictions stemming from it to future research.

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The proof proceeds as follows: we first prove that both constraints are binding. Then that $w_K > w_F = 0$, then that $K_U > 0$ and $K_D w_K \geq 0$.

1. Both constraints are binding.

To see this, consider programme $\mathcal{P}^E$ and suppose that the no-mimicking condition (2.9) is slack. Then, provided that the expected returns are non-decreasing in the rating outcome, i.e., $E_U \geq E_D$,[12] also the participation constraint (2.8) is slack, given that, by Assumption 1, the left hand side of the participation constraint is greater than the left hand side of the no-mimicking condition. It would then be possible to increase the CEO return by raising both E_U and E_D, while still satisfying the participation constraint.

The individual rationality constraint (2.8) is also binding. If not, it would be possible from programme $\mathcal{P}^E$ to raise E_U and lower E_D so as to keep the no-mimicking condition binding and increase the CEO return. The variation in E_D necessary to satisfy the no-mimicking condition is

$$dE_D = -\frac{q_H}{q_L} dE_U. \tag{2.a}$$

The effect of such variations on the participation constraint is $dPC = -r_H dE_U - r_L dE_D$, which, using (2.a), becomes $dPC = -\frac{1}{q_L}\left(r_H q_L - r_L q_H\right) dE_U$. This is strictly negative, given that coefficient of dE_U is the correlation index between signal and type. The effect on the objective function is identical but with opposite sign.

[12] We will ex-post check that this is indeed the case.

2. $w_K > w_F = 0$. Suppose not, i.e., suppose $w_K = w_F$ and suppose in programme $\mathcal{P}^{RA}$ to raise w_K and lower w_F in such a way to keep the CEO's profit function and the shareholders participation constraint unchanged:

$$dw_K = -\frac{[r_H (1 - K_U) + r_L (1 - K_D)]}{r_H K_U} dw_F. \tag{2.b}$$

The effect of such variations in the no-mimicking condition is $dNM = q_H dE_U + q_L dE_D$, which, using (2.b), becomes $dNM = \frac{1}{r_H} (r_H q_L - q_H r_L)(1 - K_D) dw_F$, which is strictly negative. This goes on until w_F falls to zero and $w_K > 0$.

3. $K_U = 1$, $K_D \geq 0$, $w_K > 0$.

To show this, we use $w_F^* = 0$ in the optimization problem $\mathcal{P}^{RA}$. This becomes:

$$\max p_G (r_H K_U + r_L K_D) w_K \tag{2.c}$$

$$p_G (y - r_H K_U w_K - r_L K_D w_K - c) = I \tag{2.d}$$

$$V^B = p_B (q_H K_U + q_L K_D) w_K \tag{2.e}$$

Suppose $K_U = K_D \in (0, 1)$ and suppose to raise K_U and lower K_D in such a way to keep the CEO's profit function and the shareholders participation constraint unchanged:

$$dK_U = -\frac{r_L}{r_H} dK_D. \tag{2.f}$$

The effect of such variations in the no-mimicking condition is $dNM = q_H dK_U + q_L dK_D$, which, using (2.f), becomes $(q_L r_H - q_H r_L) \frac{w_K}{r_H} dK_D < 0$, which is strictly negative. Thus, $1 > K_U > K_D > 0$.

We next show that $K_U = 1$. Suppose not. Then, it is possible to raise K_U and lower

w_K in such a way to keep the CEO's profit function and the shareholders participation constraint unchanged:

$$dK_U = -\frac{r_H K_U + r_L K_D}{r_H w_K} dw_K \tag{2.g}$$

The effect of such variations in the no-mimicking condition is $dNM = q_H w_K dK_U + (q_H K_U + q_L K_D)\, dw_K$, which, using (2.g), becomes $\dfrac{p_B}{r_H} K_D (r_H q_L - q_H r_L)\, dw_K$, which is negative. Thus, $K_U = 1$.

Solving the binding constraints (2.d) and (2.e):

$$K_D^* = \frac{p_G r_H (p_B y - I) - p_B q_H [p_G (y - c) - I]}{p_B q_L [(p_G y - c) - I] - p_G r_L (p_B y - I)},$$
$$w_K^* = \frac{q_L \dfrac{1}{p_G} [p_G (y - c) - I] - r_L \dfrac{1}{p_B} (p_B y - I)}{(r_H q_L - r_L q_H)}.$$

From K_D^* we obtain the probability of being replaced upon a downgrade F_D^* (2.5) reported in Proposition 1. By Assumption 1, F_D^* is positive. Moreover, by Assumption 2, the denominator is larger than the numerator, which implies that $F_D^* < 1$. This in turn also implies that $K_D^* < 1$. As regards w_K^*, this is also positive. Indeed, the denominator is positive because of the positive correlation between signal and type. The numerator is also positive by Assumption 1.

Using K_U^*, K_D^* and w_K^* in the objective function (2.c), the CEO return becomes $[p_G (y - c) - I] = V^G - p_G c$.

Last, by comparing the good type CEO compensation contract with replacement with the one obtained by the bad type under a tenured contract, $w_B = \dfrac{1}{p_B} (p_B y - I)$, we see that $w_K^* > w_B$ iff:

$$\frac{1}{p_G} [p_G (y - c) - I] > \frac{1}{p_B} (p_B y - I)$$

which certainly holds under Assumption 1.

Last, we check that the CEO expected return is non-decreasing in the rating outcome, i.e., $E_U^* \geq E_D^*$. To show this, recall that $E_U^* = K_U^* w_K^* + (1 - K_U^*)\, w_F^*$ and $E_D = K_D^* w_K^* + (1 - K_D^*)\, w_F^*$. Using $w_F^* = 0$, $K_U^* = 1$, it follows that $E_U^* = w_K^*$, and $E_D^* = K_D^* w_K^*$. Since K_D^* is strictly lower than 1, it follows that $E_U^* > E_D^*$.

REFERENCES CITED

1. Adam J. C. and S. A. Mansi, 2009. *CEO turnover and bondholder wealth*, Journal of Banking and Finance 33, 522-533.

2. Alali F. A. Anandarajan and W. Jiang, 2012. *The effects of corporate governance on firm's credit ratings: Further evidence using governance score in the United States*, Accounting and Finance 52, 291-312.

3. Barucci E., C. Bianchi and M. Frediani, 2006. Giornale degli Economisti e Annali di Economia 65, Nuova Serie, 127-154.

4. Bebchuk L., A. Cohen and A. Ferrell, 2008. *What matters in corporate governance?*, Review of Financial Studies 22, 783-827.

5. Berger P., E. Ofek and D. Yermack, 1997. *Managerial entrenchment and capital structure decisions*, Journal of Finance 52, 1411-1438.

6. Blackwell D. W., J. A. Brickley and M. S. Weisbach, 1994. *Accounting information and internal evaluation: Evidence from Texan banks*, Journal of Accounting and Economics 17, 331-359.

7. Brickley J. A., 2003. *Empirical research on CEO turnover and firm-performance: A discussion*, Journal of Accounting and Economics 36, 227-233.

8. Brown, L. D. and M. L. Caylor, 2006. *Corporate Governance and Firm Valuation*, Journal of Accounting and Public Policy 25, 409-434.

9. Chakraborty, A., S. Sheikh, and N. Subramanian, 2009. *The relation between incentive compensation and performance related CEO turnover*, Journal of Economics and Business, 61, 295–311.

10. Chakraborty, A., and S. Sheikh, 2015. *The Pressure to Perform: Option Compensation and Forced CEO Turnover*, International Journal of Business, 20(4), 308–325.

11. Coughlan A. T. and R. M. Schmidt, 1985. *Executive compensation, management turnover, and firm performance: An empirical investigation*, Journal of Accounting and Economics 7, 43-66.

12. Covitz D. M. and P. Harrison, 2003. *Testing conflicts of interest at bond rating agencies with market anticipation: Evidence that reputation incentives dominate*, Federal Reserve Board Working Paper.

13. DeFond M. L. and C. W. Park, 1999. *The effect of competition on CEO turnover*, Journal of Accounting and Economics 27, 35-56.

14. Denis D. and A. Sarin, 1999. *Ownership and board structure in publicly traded corporations*, Journal of Financial Economics 52, 187-224.

15. Farrell K.A. and D. A. Whidbee, 2002. *Monitoring by the financial press and forced CEO turnover*, Journal of Banking and Finance 26:12, 2249-2276.

16. Fong K.Y.L., Hong H. G., Kacperczyk, Dubik J. D., 2014, *Do Security Analysts Discipline Credit Rating Agencies?*, AFA 2013 San Diego Meeting Paper.

17. Gibbons R.S. and K.K. Murphy, 1990. *Relative performance evaluation for chief executive officers*, Industrial and Labor Relations Review 43, 30S-51S.

18. Gompers P., J. Ishii and A. Metrick, 2003. *Corporate governance and equity prices*, Quarterly Journal of Economics, 118, 107-155.

19. Haley P. M., K. G. Palepu, R. S. Rubak, 1990, *Does Corporate Governance Improve After Mergers?*, NBER Working Paper No. 3348.

20. Hermalin, B.E., and M.S. Weisbach, 1998. *Endogenously chosen boards of directors and their monitoring of the CEO*, American Economic Review, 88(1), 96–118.

21. Jenter D. and K. Lewellen, 2014. Working Paper No. 3054.

22. Jenter D. and F. Kanaan, 2014. *Performance-induced CEO turnover*. Journal of Finance (forthcoming).

23. Kang J. and A. Shivdasani, 1995. *Firm performance, corporate governance and top executive turnover in Japan*, Journal of Financial Economics 38, 29-58.

24. Kang Q. and Q. Liu, 2009. *Credit rating changes and CEO incentives.*

25. Lehn K. M. and M. Zhao, 2006. *CEO turnover after acquisitions: Are bad bidders fired?*, Journal of Finance 61, 1759-1811.

26. Malatesta, P.H. and R.A. Walkling, 1988. *Poison pills securities. Stockholder wealth, profitability, and ownership structure.* Journal of Financial Economics 20, 347-376.

27. Manne H., 1965. *Mergers and the market for corporate control*, Journal of Political Economy 73, 110-120.

28. Mikkelson W.H. and M. M. Partch, 1997. *The decline of takeovers and disciplinary managerial turnover*, Journal of Financial Economics 44, 205-228.

29. Murphy K J. and J. L. Zimmerman, 1993. *Financial performance surrounding CEO turnover*, Journal of Accounting and Economics 16, 273-315.

30. Parrino R., 1997. *CEO turnover and outside succession: A Cross-Sectional Analysis*, Journal of Financial Economics 46, 165-197.

31. Spence, A.M., 1973. *Job market signaling*, Quarterly Journal of Economics, 87, 355–374.

32. Spence, A.M., 1974. Market signaling, information transfer in hiring and related processes, Harvard University Press, Cambridge.

33. Kato T. and C. Long, 2006. CEO turnover, firm performance and enterprise reform in China: evidence from new micro data, IZA Discussion Papers, No. 1914.

34. Warner J. B., R. L. Watts and K. H. Wruck, 1988. Stock prices and top management changes, Journal of Financial Economics 20, 461-492.

35. Weisbach M. S., 1988. Outside directors and CEO turnover, Journal of Financial Economics 20, 431-460.

Table 2.1: Summary statistics

Means, standard deviations, minimums and maximums for specific firm characteristics for the entire sample. Firm specific characteristics include: Leverage, Size, Tangibility, Market-to-Book Ratio, Profitability and S&P rating levels. CEO specific characteristics include: Total compensation, Total bonus, Total salary, Tenure, Age. The sample period goes from 1998 to 2014. The total number of firms is 653.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Size	8.849	1.272	5.065	13.649	17214
Leverage	0.301	0.154	0	1.591	17214
Profitability	0.09	0.067	-0.58	0.821	17214
Market to Book	1.652	1.026	0.439	29.11	17214
Tangibility	0.378	0.252	0	0.967	17214
S&P	14.671	2.971	1	23	17214
Compensation	8.67	0.873	3.689	13.393	17190
Bonus	6.675	1.167	0	11.251	5895
Salary	6.819	0.414	1.099	8.294	17154
CEO	6.44	6.145	0	43	17186
Age	56.536	6.281	35	87	17214

Table 2.2: Summary statistics: Firms with Entrenched and Non-Entrenched CEOs

Means, standard deviations, minimums and maximums for specific firm characteristics between weakly entrenched and strongly entrenched firms. Strongly entrenched firms are defined as firms whose median number of anti-taleover provisions, as described in Bebchuck, Cohen and Ferrell (BCF, 2004), is greater than the median across the entire sample. Weakly entrenched firms are defined as firms whose median number of anti-takeover provisions is below the sample median. Firm specific characteristics include: Leverage, Size, Tangibility, Market-to-Book Ratio, Profitability and S&P rating levels. CEO characteristics include: Total compensation, Total salary, Total bonus, Tenure and Age. The total number of firms across the sample is 653. Among these firms, 364 can be classified as weakly entrenched and 289 as strongly entrenched. The sample period goes from 1998 to 2014.

	Weakly entrenched					Strongly entrenched				
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Size	9.117	1.368	5.065	13.649	9200	8.541	1.072	5.686	12.156	8014
Leverage	0.301	0.16	0	1.591	9200	0.301	0.147	0	1.129	8014
Profitability	0.092	0.069	-0.58	0.821	9200	0.088	0.065	-0.432	0.655	8014
Market to Book	1.71	1.153	0.526	29.11	9200	1.586	0.851	0.439	16.133	8014
Tangibility	0.38	0.251	0	0.954	9200	0.375	0.254	0.002	0.967	8014
S&P	14.818	3.225	1	23	9200	14.501	2.641	5.333	23	8014
Compensation	8.745	0.911	3.76	11.739	9184	8.583	0.819	3.689	13.393	8006
Bonus	6.788	1.147	0	9.909	3331	6.528	1.175	1.386	11.251	2564
Salary	6.853	0.425	1.966	8.294	9149	6.781	0.396	1.099	8.294	8005
Tenure	6.469	6.451	0	42	9172	6.407	5.775	0	43	8014
Age	56.738	6.357	35	87	9200	56.304	6.184	39	86	8014

Table 2.3: Rating Changes and CEO Turnover

Logit regressions to estimate the probability of forced turnover following S&P rating changes, be it a downgrade or an upgrade. A managerial turnover is defined as forced if the reason behind the departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. A forced turnover is identified by a dummy variable that takes value 1 if the turnover is forced and 0 if the turnover is voluntary. Panel A shows the analysis for the entire sample. Panel B shows the analysis for firms classified as Investment Firms (i.e, with an S&P rating above the BBB-investment threshold). Column (1) studies the probability of CEO forced turnover following an S&P rating change with the inclusion of year-quarter fixed effects. Column (2) adds industry fixed effects. Columns (3) and (4) propose the same analysis of Columns (1) and (2) with the inclusion of firm and CEO specific controls like: Size, Leverage, Market to Book, Tangibility, CEO Tenure, Total Compensation, Total Salary, CEO Age and CEO Gender. All the control variables are lagged one period. Columns (5) and (6) refine the dependent variable to distinguish between internal and external turnovers. An internal turnover is identified by a dummy variable that takes value 1 if the new CEO is chosen within the firm that has received the credit rating change, be it an upgrade or a downgrade. An external turnover is identified by a dummy variable that takes value 1 if the new CEO is chosen outside the firm that has received the credit rating change. Columns (5) and (6) include year/quarter as well as industry fixed effects. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Forced				**External**	**Internal**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Entire Sample						
Downgrade S&P	1.213***	1.177***	1.116***	0.998***	1.944***	0.576*
	(0.252)	(0.255)	(0.267)	(0.273)	(0.436)	(0.330)
S&P	-0.0978***	-0.102***	-0.148***	-0.125***	-0.251***	-0.0728
	(0.0292)	(0.0350)	(0.0327)	(0.0423)	(0.0658)	(0.0524)
N	18910	17249	17462	15601	5812	12748
Panel B: Firms Above the Investment Threshold						
Downgrade S&P	1.092***	1.084**	1.118**	0.924**	2.886***	0.274
	(0.407)	(0.427)	(0.448)	(0.457)	(1.039)	(0.706)
S&P	-0.170**	-0.185**	-0.229**	-0.221**	-0.425**	-0.131
	(0.0863)	(0.0788)	(0.102)	(0.101)	(0.190)	(0.134)
N	7715	6685	6862	5703	1092	4597
Firm-CEO Controls	No	No	Yes	Yes	Yes	Yes
(Year-Quarter) FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4: Rating Changes and CEO Turnover - Entrenched versus Non-Entrenched Fims

Logit regressions to estimate the probability of forced turnover following an S&P rating change, be it a downgrade or an upgrade, between strongly entrenched and weakly entrenched firms. A CEO turnover is defined as forced if the reason behind the departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. A forced turnover is identified by a dummy variable that takes value 1 if the turnover is forced and 0 if the turnover is voluntary. Panel A shows the analysis when managerial entrenchment is defined following Bebchuck, Cohen and Ferrell (BCF, 2004). Panel B shows the analysis when managerial entrenchment is defined following Gompers, Ishi and Metrick (GIM, 2003). Columns (1) and (2) refer to firms classified as strongly entrenched. Strongly Entrenched firms are defined as those whose median number of anti-takeover provisions, following either BCF (2004) or GIM (2003), is greater than the sample median. Columns (1) and (2) study the probability of CEO forced turnover following an S&P rating change with the inclusion of year-quarter fixed effects and industry fixed effects with and without firm and CEO-specific controls like: Size, Leverage, Market to Book, Tangibility, CEO Tenure, Total Compensation, Total Salary, CEO Age and CEO Gender. All the control variables are lagged one period. Columns (3) and (4) repeat the same analysis presented in Columns (1) and (2) for weakly entrenched firms. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The sample period covered for this analysis goes from 1998 until 2014.

	Strongly entrenched		**Weakly Entrenched**	
	(1)	(2)	(3)	(4)
	Forced	**Forced**	**Forced**	**Forced**
Panel A: BCF (2004) index of Entrenchment				
Downgrade S&P	0.942	0.576	1.079***	0.997**
	(0.604)	(0.619)	(0.371)	(0.394)
S&P	-0.0615	-0.0901	-0.123**	-0.173**
	(0.0932)	(0.129)	(0.0510)	(0.0711)
N	4063	4040	6360	5881
Panel B: GIM (2003) index of Entrenchment				
Downgrade S&P	1.695**	0.520	1.642***	1.381***
	(0.808)	(0.845)	(0.459)	(0.530)
S&P	0.0197	0.235	-0.130**	-0.126
	(0.111)	(0.367)	(0.0613)	(0.106)
N	1171	1166	1711	1564
Firm-CEO Controls	No	Yes	No	Yes
(Year-Quarter) FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes

Table 2.5: CEO Turnover - Heckman Probit estimation

Heckman Probit estimation in which the probability of being replaced following a credit rating change, be it a downgrade or an upgrade, is predicted with selection determined on whether the CEO is weakly entrenched. Part (1) of the table shows the results of a Heckman Probit model in which the probability of forced turnover (Forced) is regressed against past rating changes. Weakly entrenched shows the first-stage estimation of the Heckman model in which the probability of being unentrenched, conditioning on a set of explanatory variables (Firm size, Firm leverage, Firm profitability, CEO tenure, CEO salary, CEO age), is estimated by using a probit model. Part (2) of the table provides the same analysis shown in Part (1) by adding firm and CEO-specific controls like: Size, Leverage, Profitability, CEO Tenure, Total Salary, CEO Age, Market to Book and Tangibility. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The sample period covered for this analysis goes from 1998 to 2014.

	(Part 1)		(Part 2)	
	Weakly entrenched	**Forced**	**Weakly entrenched**	**Forced**
Upgrade S&P		-3.980		-4.474
		(1131.8)		(357.6)
Downgrade S&P		0.512***		0.500***
		(0.139)		(0.147)
S&P		-0.0394***		-0.0599***
		(0.0152)		(0.0215)
Size	0.360***		0.359***	0.0971*
	(0.0122)		(0.0122)	(0.0511)
Leverage	-0.163**		-0.161**	-0.923**
	(0.0794)		(0.0794)	(0.388)
Profitability	0.422**		0.429**	-1.815**
	(0.168)		(0.168)	(0.909)
CEO Tenure	0.00147		0.00149	-0.0107
	(0.00208)		(0.00208)	(0.00886)
Salary	-0.284***		-0.281***	-0.143***
	(0.0353)		(0.0353)	(0.0517)
CEO Age	0.00814***		0.00804***	0.0226***
	(0.00198)		(0.00198)	(0.00861)
N	16758	16758	16758	16758
(Year-Quarter) FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes

Table 2.6: Rating Changes and CEO Turnover - High Versus Low Investment Firms

Logit regressions to estimate the probability of forced turnover following an S&P rating change, be it a downgrade or an upgrade, between firms with high investment levels and firms with low investment levels. Investment is defined as the ratio of capital expenditures over quarterly sales. Firms with high (low) levels of investment are defined as those whose median investment is greater (smaller) than the industry median. A CEO turnover is defined as forced if the reason behind the departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. A forced turnover is identified by a dummy variable that takes value 1 if the turnover is forced and 0 if the turnover is voluntary. Columns (1) and (2) refer to firms with high levels of investment and study the probability of CEO forced turnover following an S&P rating change with the inclusion of year-quarter fixed effects and industry fixed effects, with and without firm and CEO-specific controls like: Size, Leverage, Market to Book, Tangibility, CEO Tenure, Total Compensation, Total Salary, CEO Age and CEO Gender. All the control variables are lagged one period. Columns (3) and (4) replicate the analysis for firms with a low investment levels. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The sample period covered for this analysis goes from 1998 until 2014. Coefficients for CEO Tenure and Tangibility are not reported.

	Low-Investment		**High-Investment**	
	(1)	(2)	(3)	(4)
	Forced	**Forced**	**Forced**	**Forced**
Upgrade S&P	-1.017	-0.942	-0.586	-0.437
	(1.030)	(1.033)	(0.710)	(0.710)
Downgrade S&P	0.685	0.714	1.350***	1.067***
	(0.420)	(0.440)	(0.326)	(0.360)
S&P	-0.109**	-0.202***	-0.0598	-0.0537
	(0.0493)	(0.0631)	(0.0465)	(0.0582)
Size		0.361**		0.371***
		(0.178)		(0.128)
Leverage		-0.133		-0.158
		(1.077)		(0.976)
Profitability		-0.160		-4.576**
		(1.347)		(2.210)
Market to Book		0.0457		-0.744***
		(0.123)		(0.282)
Salary		0.00412		-0.0938
		(0.0592)		(0.0954)
CEO Age		0.0471*		0.0464
		(0.0274)		(0.0333)
N	6787	6565	10419	9682
(Year-Quarter) FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes

Table 2.7: Rating Changes and CEO Turnover - High-Fee versus Low-Fee fims

Logit regressions to estimate the probability of forced turnover following an S&P rating change, be it a downgrade or an upgrade, between high-fee firms and low-fee firms. A CEO turnover is defined as forced if the reason behind the departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. A forced turnover is identified by a dummy that takes value 1 if the turnover is forced and 0 if the turnover is voluntary. Columns (1) and (2) refer to high-fee firms. High-Fee firms are defined as whose whose median number of bonds issued is greater than the sample median. Columns (1) and (2) study the probability of CEO forced turnover following an S&P rating change with the inclusion of year-quarter fixed effects and industry fixed effects with and without firm and CEO-specific controls like: Size, Leverage, Market to Book, Tangibility, CEO Tenure, Total Compensation, Total Salary, CEO Age and CEO Gender. All the control variables are lagged one period. Columns (3) and (4) repeat the same analysis presented in Columns (1) and (2) for low-fee firms. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The sample period covered for this analysis goes from 1998 until 2014.

	High-Fee		**Low-Fee**	
	(1)	(2)	(3)	(4)
	Forced	**Forced**	**Forced**	**Forced**
Downgrade S&P	0.334	0.179	0.838*	0.951**
	(0.658)	(0.717)	(0.450)	(0.469)
S&P	-0.201***	-0.277*	-0.0771	-0.0751
	(0.0755)	(0.146)	(0.0703)	(0.109)
Size		-0.0232		0.0395
		(0.388)		(0.227)
Leverage		-5.197		-0.820
		(3.772)		(2.025)
Profitability		-4.056		-0.807
		(5.374)		(5.262)
Market to Book		-3.053*		-0.737
		(1.777)		(0.497)
Tangibles		1.909		-0.598
		(3.338)		(1.920)
Tenure CEO		0.122		-0.0398
		(0.0889)		(0.0551)
Salary		0.0433		0.0885
		(0.182)		(0.142)
Age CEO		0.123*		0.104*
		(0.0719)		(0.0542)
N	1754	1732	2387	2159
(Year-Quarter) FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes

Table 2.8: Rating Changes and CEO Turnover - Financial Crisis

Logit regressions to estimate the probability of forced turnover following an S&P rating change, be it a downgrade or an upgrade, before and after the 2007 financial crisis. A CEO turnover is defined as forced if the reason behind the departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. A forced turnover is identified by a dummy variable that takes value 1 if the turnover is forced and 0 if the turnover is voluntary. Columns (1) and (2) refer to the Pre-Crisis period. Columns (3) and (4) refer to the Post-Crisis period. The Post-Crisis period is identified by a dummy that takes a value equal to 1 starting from July 2009. Columns (1) and (3) study the probability of CEO forced turnover following S&P rating changes with the inclusion of year-quarter fixed effects and industry fixed effects. Columns (2) and (4) add firm and CEO-specific controls like: Size, Leverage, Profitability, Market to Book, Tangibility, CEO Tenure, Total Salary, CEO Age. All the control variables are lagged one period. Business Cycle variables are included in all the specifications. Business Cycle variables include: S&P 500 market returns, S&P 500 price levels, past stock market performance, past GDP, industry asset turnover growth. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The sample period covered for this analysis goes from 1998 until 2014. Coefficients for Tangibility and Tenure CEO are not reported.

	Pre-Crisis		**Post-Crisis**	
	(1)	(2)	(3)	(4)
	Forced	**Forced**	**Forced**	**Forced**
Downgrade S&P	1.254***	1.045***	1.111*	0.915
	(0.296)	(0.309)	(0.669)	(0.696)
Upgrade S&P	-1.040	-0.941	0.134	0.204
	(1.015)	(1.018)	(0.769)	(0.784)
S&P	-0.0553	-0.104**	-0.152**	-0.204**
	(0.0407)	(0.0506)	(0.0716)	(0.0979)
Size		0.445***		0.470**
		(0.124)		(0.225)
Leverage		-0.0938		-0.516
		(0.995)		(1.695)
Profitability		-2.460**		-6.844
		(1.248)		(4.482)
Market to Book		-0.219		-0.314
		(0.167)		(0.525)
Salary		-0.0142		-0.00256
		(0.102)		(0.0898)
Age CEO		0.0419**		0.0530
		(0.0193)		(0.0340)
N	12479	12366	3909	3895
Business Cycle Variables	Yes	Yes	Yes	Yes
(Year-Quarter) FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Ticker Clustered SE	Yes	Yes	Yes	Yes

Table 2.9: Instrumental Variable Analysis

Instrumental Variable Analysis for the effects of credit rating downgrades on forced CEO turnover. Columns (1) and (2) show the first stage regression results where the endogenous variable, credit rating downgrade, is regressed against two instruments, Pessimistic Equity Analysts and Analyst Coverage, and firm specific controls. Pessimistic Equity Analysts is a dummy that takes value 1 if, for every year-quarter, the firm is covered by more pessimistic equity analysts than optimistic ones. An equity analyst is defined to be pessimistic if his/her equity recommendation is below the average recommendation assigned by all equity analysts. Analyst Coverage is defined as the number of equity analysts covering a firm for every year-quarter. Firm-specific controls include: Size, ROA, Leverage, Market to Book, Tangibility, Rating Level, Cash Ratio. Columns (1) and (2) are estimated using a linear probability model. Columns (3) to (5) illustrate the second stage regression results where forced turnover is regressed against the instrumented credit rating downgrade, with the inclusion of firm and CEO-specific controls. Forced turnover is identified by a dummy that takes value equal 1 if the turnover is forced and zero if the turnover can be classified as voluntary. A managerial turnover is defined as forced if the CEO departure can be ascribed to: pressure from the board of directors, forced resignation, scandal, reorganization, demotion, personality disagreement, poor firm performance and retirement before 60. CEO-specific controls include: CEO Tenure, Total Compensation, Total Salary, CEO Age and CEO Gender. All the control variables are lagged one period. Columns (3) and (4) use a linear probability model. Column (5) uses a control function approach. In Column (5), $\widetilde{DowngradeS\&P}$ identifies the residuals from the corresponding first stage. Year and Industry fixed effects are considered in all the above specifications. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	First Stage Regression		**Second Stage Regression**		
	(1)	(2)	(3)	(4)	(5)
	Downgrade S&P	Downgrade S&P	Forced	Forced	Forced
Pessimistic Equity Analysts	0.00671**	0.00783**			
	(0.00313)	(0.00311)			
Analyst Coverage	0.00466***	0.00359***			
	(0.000623)	(0.000670)			
Downgrade S&P			0.185***	0.203***	21.49**
			(0.0485)	(0.0672)	(8.646)
					(0.13)
$\widetilde{DowngradeS\&P}$					-20.19**
					(8.676)
					(-0.122)
F test for Relevant Instruments	28.56	16.16			
p-value J test for Exogenous Instruments			0.255	0.292	0.269
N	21229	20917	21229	20528	17593
Firm Specific Controls	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes
Control Function Approach	No	No	No	No	Yes

CHAPTER 3.
ISSUER VERSUS INVESTOR-PAID RATING AGENCIES, EQUITY ANALYSTS, AND THE INFORMATION FLOW TO THE STOCK AND BOND MARKETS

3.1 Introduction

Following the financial crisis, credit rating agencies' reputation was undermined as they were often criticized for issuing untimely and inaccurate ratings. Critics argue that the compensation structure of many rating agencies that are paid by bond issuers generates conflicts of interests that lead raters to inflate issuers' ratings scores. Equity analysts, on the other hand, seemed to adjust their forecasts more quickly with the onset of the financial crisis (Sidhu and Tan 2011). This could in part explain why they did not face similar scrutiny to the credit rating agencies following the financial crisis. Equity analysts and credit rating agencies (CRAs) have the same objective of providing valuations of firms' performance to investors. However, while bond raters provide assessment of the bonds' default risk, equity analysts are concerned with firms' equity performance, which includes assessments of firms' possibility of asset appreciation and dividend payouts.

The literature has investigated the information flows between equity analysts and credit rating agencies to better understand which one provides more precise and timely recommendations. Ederington and Goh (1998) suggest that credit rating agencies and equity analysts influence each others recommendations. Ederington and Yawitz (1987), on the other hand, show that credit ratings affect equity analysts' recommendations. They argue that given that credit rating agencies have access to information that is not available to equity analyst researchers, the analysts have an incentive to utilize the unique information available to rating agencies by following any of their changes. Finally, Fong et al. (2014) show that analyst coverage is likely to have a disciplining effect on credit rating agencies.[1] They argue that the larger is the number of equity analysts monitoring a firm, the lower is the asymmetric information between firm's managers and investors. This, in-turn, puts greater the pressure on credit rating agencies to provide reliable ratings.

While the literature has addressed the information flows between issuer-paid rating agencies and equity analysts, the impact of credit ratings issued by CRAs that are compensated by investors (investor-paid raters) on these information flows has not been studied. The investor-paid rating model gained popularity because it alleviates the conflicts of interests between issuers and the rating agencies. Since the raters are compensated by investors, they do not face pressure by bond issuers to inflate their ratings. Therefore, investor-paid credit ratings are believed to be timelier, more informative, and accurate in predicting default risk (Jiang et al., 2012, Cornaggia and Cornaggia, 2013).

In this paper, we evaluate the information content of signals by investor and issuer paid rating agencies, as well as equity analyst recommendations. Specifically, we investigate whether investor-paid rating agencies provide more informative and timely ratings than issuer-paid rating agencies and equity analysts. Further, we evaluate how the bond and stock markets respond to changes in valuations provided by issuer and investor paid rating agencies, as well as equity analysts. Next, we turn to studying the impact of bond ratings and analysts' recommendations on firms' investment decisions.

[1] Analyst coverage is defined as the number of equity analysts monitoring a firm

Then, we evaluate how rating agencies and equity analysts respond to firms' leverage changes, and whether disagreement between equity analysts about firm performance translates into great disagreement in ratings issued by CRAs.

We conduct five tests to address the aforementioned empirical questions. First, we investigate who is the main information driver among the three financial gatekeepers (i.e., issuer-paid rating agencies, investor-paid rating agencies and equity analysts). Specifically, we evaluate whether a change in any of these evaluations is able to trigger changes, of the same sign, in other evaluations. We find that investor-paid ratings impact signals by issuer-paid CRAs and equity analysts. This result is driven in-part by those investor-paid rating agencies being the first to make adjustments to their signals to reflect market conditions.

Second, we study the response of the bond and stock markets to issuer-paid and investor-paid rating changes, as well as to equity analyst recommendation adjustments. We find that bond investors are more responsive to ratings issued by the credit rating agencies, while equity investors are more susceptible to recommendations by equity analysis. These results are consistent with the hypothesis outlined in Merton (1987) that it is costlier for stock market investors to pay attention to bond analysts relative to paying attention to stock analyst forecasts. Conversely, it is costlier for bond market investors to pay attention to stock analysts rather than bond analysts. Investors in firms that have a high probability of default, however, respond more to investor-paid ratings than to signals by equity analysts or issuer-paid rating agencies.

Third, we investigate how rating agencies and equity analysts respond to changes in leverage. The intuition behind this test relies on the different objectives of rating agencies and equity analysts. Rating agencies focus on predicting bonds' default risk, while equity analysts focus on firms' equity performance. Consistently, we find that increases in leverage lead to lower ratings by CRAs, and more favorable recommendations by equity analysts due to firms' additional liquidity resulting from bond issuance. Specifically, investor-paid ratings perceive an increased leverage as an increase in the probability of default, which leads to lower rating. On the other hand, equity analysts react positively to an increase in leverage being less concerned about default and more about liquidity and cash flow growth.

Fourth, we study how firms adjust their investment levels following issuer-paid and investor-paid rating changes as well as equity analyst recommendation adjustments. We find that firms' investment decisions are in-line with changes of ratings by investor-paid rating agencies. This result is consistent with investor-paid CRAs being perceived to produce timelier and more reliable signals. Lastly, we investigate whether disagreement between equity analysts about firm performance translates into disagreements in ratings assigned by issuer-paid and investor-paid CRAs. We find that heterogeneity in beliefs among equity analysts is correlated with heterogeneity in beliefs among bond rating agencies.

The aforementioned tests utilize data on S&P ratings from Compustat (as representatives of the issuer-paid rating agencies), Egan and Jones ratings obtained directly from the Egan-Jones Ratings Company (as representatives of the investor-paid CRAs), and equity analyst recommendations from the Institutional Brokers' Estimate System (I/B/E/S) database.

The paper is organized as follows. *Section 1* presents an overview of the literature. *Section 2* outlines the hypotheses tested throughout the paper. *Section 3* describes the data. *Section 4* describes the empirical results. *Section 5* concludes.

3.2 Related Literature

Literature has largely studied the capability of financial intermediaries to convey information to capital markets. Particular attention has been devoted to the role of equity analysts and credit rating agencies as well as to their interaction on the capital markets.

Regarding the role of equity analysts, a big effort has been exerted to study the real effects of the information they provide. Verrecchia (1996) shows the informational role of security analysts in increasing firm value, Womack (1996) illustrates the capability of equity analysts to increase firm visibility, Brennan and Subrahmanyan (1995) and Roulstone (2004) provide evidence of the link between analyst following and increased liquidity of firms' securities. The informative power of equity analysts is often compared to the one of credit rating agencies. Although dealing with different assets and clients, several studies (Beyer et al., 2010; Fong et al., 2014) argue that sell-side equity analysts and credit rating agencies are competitors. They both provide information to the market and, although for different reasons, they both have an incentive to issue optimistic evaluations. Sell-side equity analysts have a tendency to assign optimistic stock recommendations to curry favour with the management (Lin and McNichols, 1998; Ertimur et al., 2011). On the other side, rating agencies have largely been accused of biasing their ratings optimistically on corporate debt (Becker and Milbourn, 2011; Kraft, 2011) and structured finance projects (Lynch, 2009; Riddiough and Zhu, 2010) to generate business. Which financial intermediary, between equity analysts and credit rating agencies, is able to deliver more timely and precise information is an open question that the literature has tried to address from different angles. Batta and Muslu (2011) compare the company adjusted reported earnings released by credit rating agencies with those of equity analysts to point out that, although both informative, adjusted earnings in equity analysts are better in predicting future earnings and cash-flows. Following Lui et al. (2007), Lui et al. (2012) shows that equity changes are timilier and have a larger overall stock price impact than credit rating changes.

A first attempt to establish a direction in the information flow between bond rating agencies and stock analysts is provided in Ederington and Goh (1998) which shows that the Granger causality flows both ways: bond downgrades are preceded by declines in actual and forecast earnings and actual earnings, as well as forecasts of future earnings, tend to fall following downgrades. Other subsequent papers try to answer the same question by focusing on the advantages that equity analysts have on rating agencies and vice-versa. Equity analyst recommendations are often thought to be more objective than the recommendations assigned by other intermediaries because of the large number of equity analysts that rate the same firm. Consequently, firms covered by many equity analysts are perceived as less opaque and thus riskier. Exploiting the idea that analyst coverage is a proxy for asymmetric information, part of the literature finds that the number of equity analysts monitoring a firm is negatively related to the firm's default risk (Cheng and Subramanyan, 2007) and is likely to reduce the optimistic bias in credit ratings[2](Fong et al., 2014). However, there is also evidence that rating agencies have access to information not available to equity analysts such as minutes of board meetings, profit breakdowns by profit and new product plans (Ederington and Yawitz, 1987). Following Jung et al. (2007), the informational advantage of credit ratings has increased starting from October 2000, when the Fair Disclosure Regulation became effective[3]. The larger information set available to credit rating agencies should lead to a greater reliance of equity analysts on rating evaluations.

As far as we are aware, current literature has focused on the interaction between equity analysts and credit rating agencies without investigating the role played by the compensation system adopted by those rating agencies. More in detail, previous works have focused on equity analysts and rating agencies paid by the rated firms (issuer-paid rating agencies). An alternative rating model is the one in which rating agencies get paid by investors (investor-paid rating agencies). The compensation structure adopted by the latter ensures a reduced exposure to conflicts of interest, a greater capability of providing timely ratings and hence, an enhanced informativeness (Jiang et al., 2012; Strobl and Xia, 2012; Cornaggia and Cornaggia, 2013; Xia, 2014). Althought studies on the performance of the two rating models have always been

[2]The disciplining effects of competition on credit rating agencies, among credit ratng agencies, are studied theoretically in Bar-Isaac and Shapiro (2011), Bolton, Freixas, and Shapiro (2012), Camanho et al. (2010), Manso (2013), Mathis et al. (2009), and Skreta and Veldkamp (2011), among others. On the empirical front Becker and Milbourn (2011) find evidence that the entry of Fitch lead to better ratings. The opposite results are reported in Doherty et al. (2012) in their analysis of entry into insurance market by A.M. Best.

[3]The Fair Disclosure Regulation introduces restrictions on the information that companies can disclose to analysts. Credit rating agencies are not subject to these limitations.

considerable, there is a gap in the literature that needs to be filled. To our knowledge, no previous paper has aimed to study the reciprocal influence of issuer-paid, investor-paid ratings and equity analyst. Similarly, literature has not compared the effects of all these recommendations on the bond and stock markets as well as their effects on corporate investment. We conduct a study on equity analysts and different rating models in the following sections.

3.3 Theory and Hypotheses

In this section, we briefly discuss the underlying theory and develop hypotheses for our empirical tests. The study investigates the idea that while equity analysts and credit rating agencies have a similar objective of evaluating firms' quality, they employ different approaches to achieve this goal. Specifically, credit rating agencies provide opinions about the firm's probability of default. Equity analysts, on the other hand, issue recommendations that reflect firm's expected stock performance. Furthermore, while Standard & Poor's (S&P) and equity analysts are compensated by firms who they provide ratings for, Egan-Jones (EJR) is compensated by investors. This suggests that EJR has less incentive to inflate ratings or be reluctant to downgrade firms' ratings.

Since issuer paid rating agencies and equity analysts face pressure to provide favorable recommendations to firms that retain their services, we hypothesize that an investor paid rating agencies such as Egan and Jones (EJR) update their ratings faster to reflect the most up-to-date information available for investors. Issuer paid rating agencies such as S&P and equity analysis may be particularly slow to update their ratings when negative information about firm performance becomes available. Thus, we test whether EJR rating changes trigger shifts in S&P ratings and equity analyst recommendations of the same direction (**H1**).

As previously mentioned, equity analysts provide recommendations about the firm's expected stock performance while the investor and issuer paid rating agencies provide ratings that reflect the probability of default on firms' bonds. Therefore, equity investors may be more responsive to equity analysts' signals while bond investors and investors in risky firms will be inclined to pay particular attention to signals by rating agencies such as EJR and S&P. Thus, we test whether equity analyst recommendations have a stronger impact on firms' equity excess returns compared to ratings by EJR and S&P (**H2**). Similarly we test whether EJR and S&P ratings have a stronger impact firms' bond spreads compared to equity analyst recommendations (**H3**).

To further investigate the stock market response to signals by rating agencies and equity analysts about firm quality, we replicate our stock market analysis for a subset of firms that are classified to be speculative (i.e., firms whose ratings are below the S&P investment grade threshold). This analysis allows us to study which of the aforementioned signals has the largest impact on the equity performance of risky firms (with higher probability of default). Thus, we test whether EJR ratings have a stronger impact on equity excess returns for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations (**H4**).

Moreover, to investigate the bond market response to the outlined signals about firms quality, we replicate our bond market analysis for firms that are classified as speculative and for firms that are crossing the investment threshold (i.e., firms that at time t-1 have a rating from Standard and Poor's equal to BBB- but are downgraded to a BB+ rating in the following period). We focus on these firms to better understand the reaction of the bond market to credit rating and equity analyst recommendation changes for poor performing firms. We expect a magnified effect of EJR rating changes on the bond spread if the analysis is restricted to firms with a high probability of default. Thus, we test whether EJR rating changes have a stronger impact on bond spreads for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations (**H5**) and if EJR rating changes have a stronger impact on bond spreads for firms that were downgraded below investment grade, in comparison S&P ratings and equity analyst recommendations (**H6**).

Credit ratings and equity analyst recommendations affect firms' financing opportunities. Higher ratings or better equity analyst recommendations translate into an easier access to capital markets, which, in turn, implies greater investment opportunities. Consequently, we evaluate whether firms internalize issuer-paid, investor-paid and equity analyst recommendation changes and, consequently, utilize these ratings for their investment decisions. If investor-paid rating agencies have greater information content, we expect to see a greater increase (decrease) in firm's investment following investor-paid upgrades (downgrades) compared to rating changes by to issuer-paid agencies such as S&P or changes in equity analyst recommendations. Thus, we test whether EJR rating changes have a stronger impact on firm investment in comparison S&P ratings or equity analyst recommendations (**H7**).

Moreover, an increase in firm's leverage is likely to lead to lower ratings scores by the credit rating agencies since it will raise the firm's probability of default. At the same time, an increase in leverage implies that a firm was able to raise more capital cost effectively on the bond market, which suggests that it has greater investment opportunities. Thus, the effect of an increase in leverage on firm's expected stock performance is ambiguous and remains an empirical question. Hence, we test whether the impact of an increase in leverage has a differential effect on S&P and EJR ratings as apposed to equity analyst recommendations and evaluate the magnitudes of these effects (**H8**).

Finally, we evaluate whether greater disagreement between equity analysts about recommendations for firm's equity performance translates into a greater disagreement between EJR and S&P ratings. The intuition is that equity analysts disagree in their assessment of equity performance about some firms more than others. This heterogeneity in beliefs about firm quality can be driven by limited or noisy of information about firm performance. Consistently, for some firms, bond rating agencies are more likely to disagree in their assessment of default risk. Thus, we test whether higher disagreement in equity analyst recommendations is associated with a higher disagreement between EJR and S&P ratings (**H9**).

Thus, in summary, in this paper we test the hypotheses below:

H1 *EJR rating changes trigger shifts in S&P ratings and equity analyst recommendations of the same direction.*

H2 *Equity analyst recommendations have a stronger impact on firms' equity excess* *returns compared to ratings by EJR and S&P.*

H3 *EJR and S&P ratings have a stronger impact firms' bond spreads compared to equity analyst recommendations.*

H4 *EJR ratings have a stronger impact on equity excess returns for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations.*

H5 *EJR rating changes have a stronger impact on bond spreads for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations.*

H6 *EJR rating changes have a stronger impact on bond spreads for firms that were downgraded below investment grade, in comparison S&P ratings and equity analyst recommendations.*

H7 *EJR rating changes have a stronger impact on firm investment in comparison S&P ratings or equity analyst recommendations.*

H8 *Increase in leverage has a differential effect on S&P and EJR ratings as apposed to equity analyst recommendations.*

H9 *Higher disagreement in equity analyst recommendations is associated with a higher disagreement between EJR and S&P ratings.*

3.4 Data and Sample Selection

The sample requires the merge of different databases that provide information on ratings, equity analysts' recommendations, firm characteristics and stock returns details.

The first step we follow is to merge the *S&P database*, the *EJR database* and the *IBES database*.

The *S&P* long-term credit ratings are obtained from Compustat North America Ratings. All the observations for which there are no rating data are deleted from the sample. Following existing literature, we assign numerical values to each rating on notch basis: AAA=23, AA+=22, AA=21, AA-=20, A+=19, A=18, A-=17, BBB+=16, BBB=15, BBB-=14, BB+=13, BB=12, BB-=11, B+=10, B=9, B-=8, CCC+=7, CCC=6, CCC-=5, CC=4, C=3, D=2, SD=1. Since firm characteristics are available only quarterly, we construct a quarterly time series for the S&P rating database. To this aim, we average the rating actions happening in the same quarter meaning that if there are more than one rating action in the same quarter, we take the average of these ratings based on the above numerical conversion. The original S&P dataset includes 4,615 firms for a total number of observations of 143,950 from 1998 until 2014.

The *EJR* database is obtained directly from the Egan and Jones Rating company. The database contains issuers' names, tickers, rating actions, including new rating assignments and related rating dates. This database is constructed on a time series basis where each credit rating with a rating action is treated as an observation.

We, thus, construct a quarterly time series for the EJR database where I assign a rating in the current quarter equal to the rating in the previous quarter if no rating action has occurred. Since EJR and S&P use the same rating scale, we use the same numerical conversion adopted for the S&P database. As before, we delete observations when rating data are not available. The original EJR database includes 2,402 firms for a total number of observations equal to 58,583 from 1999 until 2014.

We obtain all equity analyst recommendations issued between January 1993 and December 2014 from the I/B/E/S detail files. Equity analysts use a five-tier rating system. More specifically, the I/B/E/S recommendation file tracks each recommendation made by each analyst, where recommendations are standardized and converted to numerical scores where "1" denotes a *Strong Buy* recommendation, "2" denotes a *Buy* recommendation, "3" denotes a *Hold* recommendation, "4" denotes a *Underperform* recommendation and "5" denotes a *Sell* recommendation. The original I/B/E/S file provide recommendations that are analyst specific. We average all the recommendations in a given firm-year-month to get the average monthly recommendation for every firm in our sample. This delivers a sample of analysts recommendations that covers 1,799 firms for a total number of observations of 158,511 from 1994 until 2014. This database offers also the opportunity to construct a measure of heterogeneity in equity analysts beliefs. The measure, based on the standard deviation of analysts' recommendations, provides insights on how dispersed is the information they are able to provide.

The S&P, EJR and I/B/E/S databases are merged by firm ticker, year and month. The final database of equity analysts' recommendations and ratings contain

1,150 firms from 1999 until 2014.

The analysis requires additional data on Moodys' ratings. Moody's ratings are collected using the Moody's website. The rating scale adopted by Moodys is different from the S&P and EJR's one. In order to make the comparison across ratings more manageable, we convert Moodys' ratings using the following numerical conversion: Aaa=23, Aa1=22, Aa2=21, Aa3=20, A1=19, A2=18, A3=17, Baa1=16, Baa2=15, Baa3=14, Ba1=13, Ba2=12, Ba3=11, B1=10, B2=9, B3=8, Caa1=7, Caa2=6, Caa3=5, Ca=4, C=3. We collect ratings for a subset of large firms (firms whose assets are larger than 1 million). We are able to collect Moodys ratings for 286 firms. The total number of observations for the Moodys file is 3,652. The Moodys sample period goes from 2004 to 2014.

The file containing ratings and equity recommendations is augmented with financial statement and financial market data from Compustat and the Center for Research in Security Prices (CRSP).

Compustat provides firm specific variables. More precisely, by exploiting this dataset, we construct variables such as Investment, Size, Tangibility, Market-to-Book, Profitability, Long-Term Leverage, Debt Issuance and Cash-Asset ratio. Investment is defined as the ratio of Capital Expenditures over assets. Size is constructed as the log of quarterly total assets. To construct this variable, we delete observations if total assets are equal or lower than zero. Tangibility is defined as the ratio of property plant and equipment over total assets. Market-to-Book is constructed as the ratio of the market value of assets over the book value of assets, where the market value of assets is defined as the market value of equity (close price multiplied by common shares outstanding) minus the book value of equity (total assets minus total liabilities plus deferred taxes and investment tax credit) plus the book value of total assets. We delete observations if market-to-book is equal or lower than zero. Profitability is proxied by the Return on Assets, computed as operating income before depreciation over total assets. The Long-Term Leverage is given by the long-term debt over total assets. Debt Issuance is constructed as the ratio between the first difference of the firm total debt and the lagged book value of total assets. Finally, the Cash ratio is computed as the ratio of cash over total quarterly assets. Missing values for all the variables cited above are deleted. To limit the effects of outliers, all the variables are winsorized at the 1% level.

We use CRSP data to get stock information data. The use of this dataset allows to construct two main variables. First, we can define the stock market excess return for every firm in our sample by looking at the difference between the stock market return and the return on a benchmark, the *S&P500* portfolio. Second, the use of the CRSP database provides the opportunity to construct an additional measure of heterogeneity in equity analysts beliefs, the *monthly turnover.* A number of empirical papers in the finance literature (among others, Kandel and Pearson, 1995) as well as in the accounting literature (Bamber, 1987; Bamber, Barron and Stober, 1997) have used trading activity as a proxy for heterogeneous beliefs among investors. We construct the monthly turnover variable as the trading volume divided by the number of shares outstanding. This proxy is also used in Chemmanur, Loutskina and Tian (2008).

Finally, the analysis requires the use of bond data. Bond information is gathered from FINRA's Trade Reporting and Compliance Engine database (TRACE). This database contains information about bond prices, returns, yields and years to maturity. To get bond spreads, we collect the Treasury yields[4] from the US Treasury database, available online. We construct bond spreads for each firm as the difference between the bond yield of each security and the Treasury yield with comparable maturity and coupon. We drop observations if the spread is equal or lower than zero or if there are missing data.

3.5 Empirical Models and Regression Results

3.5.1 Information Flow between CRAs

A preliminary work by Ederington and Goh (1998) has shown that equity analysts and credit rating agencies influence each other, meaning that actual earnings and forecasts of future earnings trend to fall following downgrades as well as downgrades tend to fall after declines in actual and forecast earnings. The analysis conducted by Ederington and Goh focuses on a time interval that goes from January 1984 until December 1990, it neglects any difference in the compensation system adopted by CRAs and, consequently, does not allow to study how the information released by different CRAs affect equity analysts and vice-versa.

To study the information flow between issuer-paid credit rating agencies, investor paid credit rating agencies and equity analysts we will use a model in which

[4]Treasury yields are interpolated by the Treasury from the daily yield curve, which relates the yield on a security to its maturity based on the closing-market bid yields on actively traded Treasury securities in the over-the-counter market. The yield values are read from the yield curve at fixed yearly maturities: 1, 2, 3, 5, 7, 10, 20, 30 years.

S&P or EJR credit rating changes (or equity analyst recommendation changes) are regressed against past S&P and EJR rating changes as well as past equity analyst recommendations. The intuition behind this analysis relies on the need to check who is the main information provider among S&P, EJR and the equity analysts. If the idea that investor-paid credit rating agencies are more accurate and timely is true, then we should expect to see other information providers, as represented by the equity analysts and the issuer-paid credit rating agency S&P, to mimick the information sent by EJR ratings and to behave accordingly.

The specifications we use to test for the information flow among the three information providers are provided below:

$$\Delta IBES_{i,t} = \alpha + \beta_1 \Delta EJR_{i,t-1} + \beta_2 \Delta S\&P_{i,t-1} + \beta_3 \Delta IBES_{i,t-1} + \gamma_1 \Delta EJR_{i,t+1} + \\ + \gamma_2 \Delta S\&P_{i,t+1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \quad (3.1)$$

$$\Delta EJR_{i,t} = \alpha + \beta_1 \Delta IBES_{i,t-1} + \beta_2 \Delta S\&P_{i,t-1} + \beta_3 \Delta EJR_{i,t-1} + \gamma_1 \Delta IBES_{i,t+1} + \\ + \gamma_2 \Delta S\&P_{i,t+1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \quad (3.2)$$

$$\Delta S\&P_{i,t} = \alpha + \beta_1 \Delta EJR_{i,t-1} + \beta_2 \Delta IBES_{i,t-1} + \beta_3 \Delta S\&P_{i,t-1} + \gamma_1 \Delta EJR_{i,t+1} + \\ + \gamma_2 \Delta IBES_{i,t+1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \quad (3.3)$$

Model (3.1) studies the effect of past EJR ($\Delta EJR_{i,t-1}$) and S&P ($\Delta S\&P_{i,t-1}$) rating changes on future changes in equity analyst recommendations ($\Delta IBES_{i,t}$). Model (3.2) proposes a similar analysis where the effect of past changes in equity analyst recommendations ($\Delta IBES_{i,t-1}$) and S&P rating changes ($\Delta S\&P_{i,t-1}$) on future EJR rating changes

($\Delta EJR_{i,t}$) are taken into account. Model (3.3) focuses on S&P rating changes ($\Delta S\&P_{i,t}$) and how they are affected by past equity recommendation changes ($\Delta IBES_{i,t-1}$) and EJR rating changes ($\Delta EJR_{i,t-1}$). Additionaly, all the models include lead changes of the main variables in order to better investigate the direction of the information flow. Firm specific controls, year and industry fixed effects are included as well.

Results for Model (3.1) are presented in table (3.3). Column (1) shows the effects of past rating changes, from either S&P or EJR, on subsequent changes in equity analyst recommendations. Column (2) adds firm specific controls. Column (3) considers lead values for the main test variables as specified in Column (1). Column (4) focuses on the effect of the lead variables.

As shown in Columns (1), (2) and (3), past EJR rating changes have an effect on future equity recommendation changes. More in detail, EJR credit rating changes induce equity analyst recommendation changes of the same sign. S&P rating changes play no role on the equity analyst activity. Moreover, current changes in equity recommendiations do not affect future changes in EJR or S&P. The main message it is possible to get from Table (3.3) is that analysts change their recommendations only following EJR changes. Similar analysis is shown in table (3.4) which provides results for Model (3.2). Here, the dependent variable is represented by current changes in EJR ratings. Each column of the table has the same interpretation as before. Results suggest that EJR rating changes are independent of previous changes from either S&P or the equity analysts. The result persists when controlling for lead values and firm specific controls. Finally, results for Model (3.3) are presented in table (3.5). Now, the dependent variable is represented by current changes in S&P ratings. The table illustrates that S&P follows all the signals available but it is not able to impact any of them.

Taken together, the results illustrate that EJR ratings are able to affect both S&P ratings and equity analyst recommendations. Equity analyst recommendations affect S&P ratings, but the credit rating changes of the latter have no power in generating subsequent changes in either EJR ratings or equity recommendations.

3.5.2 Impact of Leverage on Equity Analyst Recommendations and Credit Rating Changes

Both equity analysts and credit rating agencies provide information about the state of firms or indutries. Both equity analysts and credit rating agencies provide this information based on a research activity that looks at the behaviour of firms' bonds and stocks together with other relevant firm specific characteristics. Although the goal of credit rating agencies and equity analists is similar (i.e. helping investors in the evaluation of firms' future prospects), the point of view assumed by equity analysts and credit rating agencies is different and translates into different job descriptions. Equity analysts elaborate recommendations about the firm's equity performance. On the other side, credit rating agencies are more interested in providing guidelines to investors about the firm's probability of default.

The different focus of equity analysts and credit rating agencies leads us to investigate what will be the effect, in terms of equity analyst recommendation changes and credit rating changes (from either S&P or EJR), of an increase/decrease in *leverage*. Intuitively, a change in leverage should affect differently the way equity analysts and credit rating agencies evaluate a firm. An increase in firm leverage might be interpreted as a way to boost the amount of cash available within the firm. Consequently, a higher level of leverage, could be interpreted *positively* from the point of view of equity analysts, who are more concerned about securities such as company shares. However, an increase in leverage can also be interpreted as a signal of the increased probability of default for the firm. A higher leverage is a signal of lower probability of repayment for the investor and, thus, might generate a *negative* assessment from credit rating agencies. As usually, we deal with two different credit rating agencies, S&P and EJR, that, because of the compensation system adopted, provide ratings that differ for accuracy and timeliness. Given that EJR is an information provider for investors, less likely to inflate and, potentially, more focused on the monitoring activity over companies, we should expect EJR to react more quickly to changes in leverage than S&P.

To capture the effects of a change in leverage on equity analyst recommendations and credit ratings we consider the following regression models:

$$\Delta IBES_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.4}$$

$$\Delta EJR_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.5}$$

$$\Delta S\&P_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.6}$$

In the above models, we regress changes in equity analyst recommendations ($\Delta IBES_{i,t}$) or changes in credit ratings ($\Delta EJR_{i,t}$, $\Delta S\&P_{i,t}$) on past changes in firm leverage ($\Delta Leverage_{i,t-1}$) as well as on firm specific characteristics. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Results are presented in table 3.6. Column (1) shows the effect of changes in leverage on subsequent changes in equity analyst recommendations. Column (2) shows the effect of changes in leverage on future EJR rating changes. Column (3) presents the effect of past leverage changes on S&P credit rating changes.

The coefficient for $\Delta Leverage_{i,t-1}$ illustrates how equity analysts and credit rating agencies perceive changes in leverage. Consistently with the intuition described above, an increase in leverage generates a greater equity analyst recommendation but a lower EJR credit rating. Put differently, an increase in the firm level of leverage generates an upgrade in equity analyst recommendations and a downgrade in EJR credit ratings. However, as pointed out in Column (3) of table 3.6, changes in leverage do not generate any subsequent change in S&P ratings. The insignificant coefficient for $\Delta Leverage_{i,t-1}$ when the dependent variable is represented by future S&P rating changes might be explained in light of the slower monitoring activity of S&P. The results confirm the idea that a higher firm leverage is interpreted differently between credit rating agencies and equity analysts and that, among credit rating agencies, S&P responds less to firm changes.

3.5.3 Impact of Rating Changes on Investment

Next, we turn to evaluate the impact of EJR, S&P, and equity analysts upgrades and downgrades on firms' investments, defined as capital expenditure as a share of assets. We average the equity analyst recommendations as well as EJR and

S&P ratings for every firm-year and merge those with annual firm characteristics publicly available from WRDS. The regression model in equation (7) evaluates the impact of rating changes on investment. The dependent variable (investment) is defined as capital expenditure over assets. Columns (1)-(3) in table 3.7, evaluate the impact of changes in ratings on investment, separately for EJR, S&P, and equity analysts recommendations (respectively), while model (4) incorporates all rating changes as independent variables. Firm controls include leverage, revenue, cash flow, as well as rating level controls for IBES, EJR, and S&P, and year and industry fixed effects. Standard errors are clustered by firm ticker.

The dummy variables $EJR_{i,t-1}^{Upgrade}$ and $EJR_{i,t-1}^{Downgrade}$ turn on when Egan and Jones average lagged annual ratings increase or decrease (respectively) by more than one rating notch. Similarly, $S\&P_{i,t-1}^{Upgrade}$ and $S\&P_{i,t-1}^{Downgrade}$ turn on when S&P ratings rise or fall (respectively) by more than one notch for firm i during year *t-1*. Consistently, equity analysts recommendations are assigned values from 1 to 5, and $IBES_{i,t-1}^{Upgrade}$, $IBES_{i,t-1}^{Downgrade}$ dummy variables refer to lagged decreases or increases (respectively) of at least one level in the average levels of equity analysts recommendations.[5]

$$\begin{aligned}\text{Investment}_{i,t}=\alpha + \beta_1\text{EJR}_{i,t-1}^{Upgrade}+\beta_2\text{EJR}_{i,t-1}^{Downgrade}+\beta_3\text{S\&P}_{i,t-1}^{Upgrade}+\beta_4\text{S\&P}_{i,t-1}^{Downgrade}+\\ +\beta_5\text{IBES}_{i,t-1}^{Upgrade}+\beta_6\text{IBES}_{i,t-1}^{Downgrade}+\gamma\text{X}_{i,t-1}+\theta_{SIC}+\theta_t+\varepsilon_{i,t}\end{aligned} \tag{3.7}$$

[5]The equity analysts recommendations are classified as follows: strong buy=1, buy=2, hold=3, sell=4, strong sell=5.

The regression results in model (1) of table 3.7 suggest that EJR upgrades lead to an average statistically significant increase of 0.45 percentage points in investment.[6] Consistently, EJR downgrades lead to a decrease of 0.62 percentage point in capital expenditure over assets. This result is consistent with the intuition that investors respond strongly to EJR rating changes since those fluctuations have substantial impact on the cost of debt, which in-turn changes the availability of cash flow for investment.

Model (2), however, suggests that only a downgrade in S&P ratings has a statistically significant impact on investment at the 1% level, while the effect of upgrade in S&P on investment is significant only at the 10% level.[7] Similarly, model (3) suggests that only downgrades of equity analysts' recommendations lead to an average decrease of 0.53 percentage points in capital expenditure as a share of assets. Finally, in model (4), we include S&P and EJR rating changes as well as changes in equity analysts' recommendations as independent variables.[8] The results suggest that Egan and Jones upgrades and downgrades lead to statistically significant increases and decreases (respectively) in the investment levels. However, only downgrades in S&P ratings and equity analysts' recommendations have a negative impact on investment that is statistically significant at 1% level.[9] Those findings suggest that investors respond strongly to Egan and Jones rating changes, and only react to downgrades

[6] Investment is defined as capital expenditure over assets.

[7] S&P downgrade leads to a decrease of 0.74 percentage points in investment, defined as capital expenditure over assets.

[8] The regression also includes firm controls such as leverage, revenue, cash flow, as well as controls for S&P and EJR rating levels and equity analysts' recommendations.

[9] The effect of upgrade is only statistically significant at the 10% level in this case

by equity analysts and S&P. Those findings reinforce the intuition that investors are highly responsive to EJR rating fluctuations since they internalize that it is an investor-paid rating agency that is accountable only to investors that retain it's services. This is in contrast to S&P, that is subjected to pressure from bond issuers to inflate their ratings, or sell-side equity analysts which are incentivized to recommend equity shares that their employer offers for sale.

3.5.3.a Impact of Upgrade/Downgrade Rating Thresholds on Investment

In addition to evaluating the impact of rating changes on investment, we also study the effect of ratings being on upgrade or downgrade thresholds on firm investment, defined as capital expenditure over assets. Similarly to Kisgen (2006), we define rating downgrade and upgrade thresholds as ratings with minus and plus signs (respectively). Firms on upgrade or downgrade rating thresholds will incur a distinct changes in their cost of the debt issuance if their ratings change. Thus to avoid a downgrade (when rating has a minus sign) or achieve an upgrade (when rating has a plus sign) firms will constrain debt issuance, to boost cash flow to equity holder, and thereby send a favorable signal to the rating agencies. Therefore, if firms constrain debt issuance when their ratings are on the boundaries, they have less free cash flow to invest in projects. Consequently, we hypothesize that when firms' ratings are on upgrade/downgrade thresholds, they may constrain investment.

We analyze the impact of rating boundaries on investment using the regression model specified in equation (3.8). The dependent variable (investment) is defined as capital expenditure over assets. $EJR^{Minus}_{i,t-1}$, $EJR^{Plus}_{i,t-1}$ are dummy variables that turn on when EJR ratings have negative or positive signs (respectively) next to the letter of the credit rating. Similarly, $S\&P_{i,t-1}^{Minus}$ and $S\&P_{i,t-1}^{Plus}$ are dummy variables for downgrade and upgrade S&P rating boundaries. The regression model also includes controls for EJR and S&P rating levels as well as equity analysts' recommendations. Additionally, the model includes firm controls for revenue, leverage, cash flow, number of employees and debt over earnings as well as industry and year fixed effects. Finally, we cluster the standard errors by firm ticker.

$$\text{Investment}_{i,t}=\alpha + \beta_1\text{EJR}_{i,t-1}^{Minus}+\beta_2\text{EJR}_{i,t-1}^{Plus}+\beta_3\text{S\&P}_{i,t-1}^{Minus}+\beta_4\text{S\&P}_{i,t-1}^{Plus}+\beta_5\text{EJR}_{i,t-1}+$$
$$+\beta_6 S\&P_{i,t-1}+\beta_7 IBES_{i,t-1}+\gamma X_{i,t-1}+\theta_{SIC}+\theta_t+\varepsilon_{i,t} \tag{3.8}$$

The regression results are depicted in table 3.8. Models (1),(2) evaluate the impact of ratings being on upgrade/downgrade boundaries on investment, separately for EJR and S&P (respectively). Model (3) incorporates coefficients for upgrade/downgrade rating boundaries for both rating agencies. The results suggest that investors are highly sensitive to upgrade and downgrade thresholds of ratings issued by Egan and Jones but not to Standard and Poor's rating boundaries. Specifically, firms constrain investment approximately 0.18 percentage points when EJR ratings have plus or minus signs. However, we find no statistical evidence to suggest that firms reduce investment when their S&P ratings are on those upgrade/downgrade boundaries. These results are consistent with the intuition that investors respond more strongly to EJR than S&P rating thresholds, since unlike Standard & Poor's, Egan and Jones is compensated by investors rather issuers, and therefore is not incentivized to inflate credit ratings in order to appease bond issuers that retain their services.

3.5.4 Impact of Rating Changes on Excess Returns

In this section, we evaluate the impact of daily changes in Egan and Jones (EJR) and standard and Poor's (S&P) credit ratings, as well as changes in the equity analysts' recommendations on firms' excess stock returns, defined as daily share returns net of the S&P500 index.

Egan and Jones and standard and Poor's primary responsibility as credit rating agencies is to predict default probabilities of firms' bonds. This implies that credit rating agencies pay special attention to evaluating the riskiness of firms with high probability of default. Thus, investors may find credit ratings to be particularly informative when they consider firms with median ratings below investment grade, as those firms are more likely to default.

Moreover, unlike S&P, EJR (Egan and Jones) is compensated by investors rather then issuers. Therefore, EJR is not subjected to pressure to inflate ratings to appease bond issuers, since is it primarily accountable to investors who pay for the firm's services. Consequently, investors may perceive EJR ratings as more accurate and thus respond more strongly when EJR rating change, which will result in larger impact of EJR than S&P changes on excess returns.

Further, equity analysts' job description differs substantially from both EJR and S&P. They provide recommendations about the firms' equity performance, rather then attempting to predict firms' default rates, which is the main responsibility of the credit rating agencies. This implies that investors in firms that are not likely to default, may find the equity analysts' recommendations about the firms' performance, to be more informative. Consequently, we hypothesize that investors in firms with low probability of default, may respond more strongly to changes in equity analysts recommendations rather then to fluctuations in EJR or S&P ratings.

To test our hypothesis, we evaluate the impact of changes in equity analysts' recommendations (changes in S&P ratings/changes in EJR ratings) on excess equity returns using the regression model specified in equation 3.9 (3.10/3.11).[10] The dependent variable $Return_{i,t} - S\&P500_{i,t}$ is the difference between firms' daily returns and S&P500 index returns. $IBES_{i,t-1}^{Upgrade}$ and $IBES_{i,t-1}^{Downgrade}$ are dummy variables that turn on when the average lagged equity analysts recommendations for firm i increase or decrease (respectively) by at least one notch. Firm controls include leverage, market to book, return on assets, as well as controls for IBES, EJR, S&P rating levels, and industry and year fixed effects. We also cluster the standard errors by firm ticker.

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 IBES_{i,t-1}^{Downgrade} + \beta_2 IBES_{i,t-1}^{Upgrade} + \gamma X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.9}$$

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 EJR_{i,t-1}^{Downgrade} + \beta_2 EJR_{i,t-1}^{Upgrade} + \gamma X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.10}$$

[10] Defined as $Return_{i,t} - S\&P500_{i,t}$

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 S\&P^{Downgrade}_{i,t-1} + \beta_2 S\&P^{Upgrade}_{i,t-1} + \gamma X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \tag{3.11}$$

In order to ensure that our assessment of the impact of changes in equity analysts' recommendations on excess returns are not driven by changes in S&P and EJR ratings, we construct a time window of 60 days prior and following changes in average analysts' recommendation where S&P and EJR levels remain constant. We identify time windows [-60,+60] such that for days [-60,-1] average analysts' recommendations remain constant, while during [0,+60], the equity analyst recommendations shift at least one notch upward or downward and remain constant afterwards.

Columns (1) and (2) in Panel A of table 3.9, depict results for the impact of equity analysts' recommendation changes on excess stock returns while S&P and EJR ratings remain constant. Similarly columns (3),(4) and (5),(6) refer to the impact of EJR and S&P changes (respectively) on excess returns while we ensure that we construct time frames [-60,+60] around changes in EJR and S&P (respectively) such that the other ratings remain constant. The regression specifications in equations (10) and (11) are similar to equation (3.9), with the exception that we replace dummy variable for equity analysts' recommendation downgrades and upgrades with dummy variables for EJR and S&P downgrades and upgrades. Regression results for the model specification in equation (3.9) are reported in columns (1) and (2) of Panel A of table 3.9. Similarly, regression results for equations (10) and (11) are reported in models (3),(4) and (5),(6) in Panel A of table 3.9.

The negative and highly significant coefficient on $IBES^{Downgrade}_{i,t-1}$ in column (2) in table 3.9 (Panel A) suggests that downgrades in equity analysts recommendations yield an average decrease of 16.4 percentage points in equity excess returns. Consistently, the positive and highly significant coefficient on $IBES_{i,t-1}^{Upgrade}$ implies that an upgrade of equity analysts' recommendations leads to an increase of 16.7 percentage points in excess returns within days [0,+60] following the change.

However, column (4) in table 3.9 (Panel A) suggests that only an EJR downgrade ($EJR_{i,t-1}^{Downgrade}$) impacts equity excess returns while EJR upgrade ($EJR_{i,t-1}^{Upgrade}$) does not have a significant effect. These results are hardly surprising since unlike equity analysts, credit rating agencies assess the riskiness of firms' default rates, and thus are likely to have a smaller impact on returns of well performing firms in comparison to equity analysts. Moreover, column (6) suggests that unlike equity analysts and Egan and Jones, S&P ratings do not have a significant impact on equity returns. These results are consistent with the idea that investors respond less to S&P ratings since they internalize that S&P is subjected to conflicts of interests with bond issuers that may impact the accuracy of their ratings.

Finally, in Panel B, we preform similar regression analyses as in Panel A, but we restrict our data sample only to firms with median S&P ratings below investment grade. In this instance, only downgrades and upgrades ($EJR_{i,t-1}^{Downgrade}, EJR_{i,t-1}^{Upgrade}$) of EJR have statistically significant impact on equity excess returns. This result is fully consistent with our intuition that investors respond strongly to EJR rating changes since EJR is an investor-paid rating agency whose main responsibility is the predict default risk, and unlike S&P, it is not subjected to pressure from bond issuers to inflate its ratings.

3.5.5 Impact of Equity Analyst Recommendations and Credit Rating Changes on Bond Market Spread

In the following section, we analyze the effect of equity analyst recommendations and credit ratings, from either S&P or EJR, on the bond market.

We analyzed the effects of credit ratings and equity analysts on the stock market. Our results illustrate that equity analyst recommendations and EJR ratings are the only signals able to affect the stock market, although the effect of EJR ratings is smaller in magnitude when compared to the equity analyst changes. A refinement of the sample to account for poor performing firms with a higher probability of default shows that only EJR rating changes affect equity excess returns.

Our goal in this section is to understand if the same pattern is observable for the bond market. The intuition behind this analysis is similar to the one that has driven the stock market analysis. We are interested in understanding which signal is more informative. The greater exposure to conflicts of interests for S&P should lead to a lower impact on the bond market. Investors discount the informativeness of S&P ratings because they know that ratings are more likely to be inflated to please the issuer. This scenario is different from the one we should observe for EJR. EJR ratings, issued for investors, are more transparent, accurate and timely and, as a consequence, should gather a greater attention (i.e. larger bond market response in terms of bond spread variation) on the bond market. What will be the effects of equity analyst recommendation changes on the bond market is an open question that we will address empirically.

The analysis we perform is based on the following model:

$$Log(Spread)_{i,t} = \alpha + \beta_1 EJR^{Downgrade}_{i,t-1} + \beta_2 EJR^{Upgrade}_{i,t-1} + \gamma_1 IBES^{Downgrade}_{i,t-1} + \gamma_2 IBES^{Upgrade}_{i,t-1} +$$

$$+ \lambda_1 S\&P^{Downgrade}_{i,t-1} + \lambda_2 S\&P^{Upgrade}_{i,t-1} + \eta X_{i,t-1} + \theta_{SIC} + \theta_t + \varepsilon_{i,t} \qquad (3.12)$$

The dependent variable of the above regression model is represented by the logarithm of the bond spread. The bond spread is defined as the difference between the security yield and the treasury (T-Bill) yield. Security yields and treausury yields are matched by maturity and coupons. The logarithm of bond spread is regressed against EJR rating changes, equity analyst recommendation changes and S&P rating changes. Firm controls, year fixed effects and industry fixed effects are included.

Results are presented in table (3.10). Table (3.10) is divided in three panels. Panel (A) considers the entire sample. Panel (B) focuses on a subset of speculative firms which are defined as firms whose average rating, from either S&P or EJR, is below the investment threshold. Panel (C) considers firms that at least once in their life experienced a rating fall from the investment-grade range to the speculative-grade range. In Table (3.10), Columns (1) and (2) describe the effects of EJR rating changes on the *log(spread)*, without and with the inclusion of firm specific controls, respectively. Columns (3) and (4) provide a similar analsysis when the EJR rating changes are replaced by the equity analyst recommendation changes. Columns (5) and (6) focus on the S&P changes. Finally, rating and equity analyst changes are considered together in the last two columns, Column (7) and Column (8).

As shown by Column (8), EJR rating upgrades and downgrades have an effect on the bond market. EJR rating upgrades reduce the bond spread by about 3.49 percentage points. EJR rating downgrades increase the bond spread by about 15.3 percentage points. As EJR downgrades, also downgrades in equity analyst recommendations have an effect on the bond market althought the magnitude is reduced (i.e. a reduction in the recommendation provided by equity analysts delivers an increase in the bond spread equal to 2.03 percentage points). Interestingly, upgrades from equity analysts do not seem to be as informative as the downgrades and, consequently, the coefficient for $IBES_{i,t-1}^{Up\,\mathrm{grad}\,e}$ is not significant. As issuer-paid credit rating agencies, also equity analysts are exposed to conflicts of interests that may compromise the credibility and the informativiness of corporate equity recommendations. Equity analysts may decide to inflate equity recommendations to please the management and protect their job. Given that an incentive to inflate ratings exists, upgrades are less reliable than downgrades.

The greater bond market response following EJR rating changes persists even after considering a subset of firms that, among the others, are more likely to default given that the assigned rating, from either S&P or EJR, is below the investment threshold (*Panel (B)*). Contrarily to what observed before, when the entire sample is taken into account, S&P rating downgrades matter. The result is not surprising and is in line with the idea that credit rating agencies care more about predicting firm default. As expected, S&P upgrades have no significant effect on the bond spread suggesting that the informativiness of S&P upgrades is reduced because of a more likely rating inflation phenomenon for this category of rating agencies.

Finally, we categorize firms in a different way in *Panel* (C). Here, we consider firms that not necessarily are poor-performing firms. However, these are riskier firms that need to be highly monitored given that, already once in their life, had a rating fall from the investment-range to the speculative one. Results suggest that only EJR rating changes are informative and affect the bond market.

The results presented in this section illustrate that the information provided by EJR is overall more informative than the one provided by S&P and the equity analysts, indipendently of the sample considered.

3.6 Conclusions

This study evaluates the discrepancies in the information content of equity analyst recommendations, and ratings by issuer and investor paid credit rating agencies. We demonstrate that Egan and Jones, the largest investor-compensated rating agency in the U.S., issues timelier ratings that impact equity analysts' recommendations and S&P ratings. This result is consistent with the intuition that being an investor-paid rating agency, EJR does not face pressure to inflate ratings or delay downgrades.

Moreover, we show that changes in credit ratings by EJR and S&P have larger impact on bond yield spreads than equity analyst recommendations. Consistently, analysts' recommendations have a larger effect on firms' equity returns. This result is in-line with the intuition that bond investors rely on bond raters to better predict default risk, while equity investors rely more on equity analysts to predict overall firm performance. Interestingly, however, when firms have a high probability of default, even equity investors rely more heavily on the investor-paid rating agency (EJR) as a predictor of default risk.

Further, we demonstrate that changes in leverage are associated with lower EJR (Egan and Jones) ratings but higher equity analyst recommendations. This result suggests that rating agencies focus on default risk, and thus will evaluate higher leverage as a negative signal. Equity analysts, on the other hand, focus on overall firm performance, and therefore will balance the cost of higher default risk with the benefit of greater liquidity resulting from bond issuance.

Finally, we find that investor-paid rating agency (EJR) has a larger impact on firms' investment decisions than equity analyst recommendations and S&P ratings. This finding can be driven by the aforementioned result that EJR rating are timelier than equity analyst recommendation and S&P ratings, or by the fact that EJR does not face pressure to inflate ratings to please issuers, and thus can be more informative for firms' investment decisions. We conclude by demonstrating that disagreement among equity analyst on their recommendations about firms' performance is correlated with greater disagreement between S&P and EJR on firms' default risks.

REFERENCES CITED

1. Bamber L. S., 1987, *Unexpected earnings, firm size and trading volume around quarterly earnings announcements*. Accounting Review 62, 510-532.

2. Bamber L. S., O. E. Barron and T. L. Stober, 1997, *Trading volume and different aspects of disagreement coincident with earnings announcements*. Accounting Review 72, 575-597.

3. Bar-Isaac H. and J. Shapiro, 2011, *Credit ratings accuracy and analyst incentives*. American Economic Review (Papers and Proceedings) 101: 120-124.

4. G. Batta and V. Muslu, 2011, *Credit rating agency and equity analysts' adjustments to GAAP earnings*.

5. Becker B. and T. Milbourn, 2011, *How did increased competition affect credit ratings*. Journal of Financial Economics 101: 493-514.

6. Bolton P., X. Freixas and J. Shapiro, 2012, *The credit ratings game*, Journal of Finance 67, 85-111.

7. Brennan M. and A. Subrahmanyam, 1995, *Investment analysis and price formation in securities markets*. Journal of Financial Economics 38: 361-381.

8. Beyer A., D. A. Cohen, T.Z. Lys and B. R. Walther, 2010, *The financial reporting environment: Review of the recent literature*. Journal of Accounting and Economics.

9. Camanho N., P. Deb, and Z. Liu, 2010, *Credit rating and competition*, London School of Economics Working Paper.

10. Chemmanur T. J., E. Loutskina and X. Tian, 2008, *The role of venture capital backing in intial public offerings: Certification, screening or market power*, Working Paper.

11. Cheng M. and K. R. Subramanyan, 2007, *Analyst following and credit ratings*, Working Paper.

12. Cornaggia J. and K. R. Cornaggia, 2013, *Estimating the costs of issuer and credit ratings*. Review of Financial Studies 26, 2229-2269.

13. Doherty N. A., A. V. Kartasheva and R. D. Phillips, 2012, *Information effect of entry into credit ratings market: The case of insurers' ratings*, Journal of Financial Economics 106: 308-330.

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

15. Ederington L. H. and J. Yawitz, 1987, *The bond rating process.* Handbook of Financial Markets and Institutions, 6th ed, E. Altman, ed. NY: John Wiley and Sons.

16. Ertimur Y., V. Muslu and F. Zhang, 2011, *Why are recommendations otpimistic? Evidence from analysts' coverage initiations*. Review of Accounting Studies.16.

17. K. Fong, H. Hong, M. Kacperczyk and J. D. Kubik, 2014, *Do security analysts discipline credit rating agencies?*, Working Paper.

18. Jiang J. X., M. G. Stanford and Y. Xie, 2012, *Does it matter who pays for bond ratings? Hostorical evidence.* Journal of Financial Economics 105, 607-621.

19. Kandel E. and N. D. Pearson, 1995, *Differential interpretation of public signals and trade in speculative markets.* Journal of Political Economy 103, 831-872.

20. Kraft P., 2011, *Do rating agencies cater? Evidence from rating-based contracts.* Working Paper, New York University.

21. Lin H. and M. McNichols, 1998, *Underwriting relationships, analysts' earnings forecasts and investment recommendations.* Journal of Accounting and Economics 25: 101-128.

22. Lui D., S. Markov and A. Tamayo, 2007, *What makes a stock risky? Evidence from Sell-Side Analysts' Risk Ratings*, Journal of Accounting Research 45 (3): 629-665.

23. Lui D., S. Markov and A. Tamayo, 2012, *Equity analysts and the market's assessment of risk*, Working Paper.

24. Lynch T., 2009, *Deeply and persistently conflicted: Credit rating agencies in the current regulatory environment.* Case Western Reserve Law Review 59: 227-304.

25. Manso, Gustavo, 2013, *Feedback effects of credit ratings*, Journal of Financial Economics 109: 535-548.

26. Mathis J., J. McAndrews and J. C. Rochet, 2009, *Rating the raters: Are reputation concerns powerful enough to discipline rating agencies?*, Journal of Monetary Economics 56: 657-674.

27. Riddiough T. J. and J. Zhu, 2010, *Shopping, relationships and influence in the market for credit ratings*. Working Paper, University of Wisconsin.

28. Roulstone D. (2003), *Analyst follwoing and market liquidity*, Contemporary Accounting Research 20 (3): 551-578.

29. Skreta V. and L. Veldkamp, 2011, *Ratings shopping and asset complexity: A theory of ratings inflation*, Journal of Monetary Economics 56: 678-695.

30. Strobl G. and H. Xia, 2012, *The issuer-pays rating model and ratings inflation: Evidence for corporate credit ratings*, mimeo.

31. Verrecchia R. E., 1996, *Impact of analyst following on stock prices and the implications for firms' disclosure policies*. Journal of Accounting, Auditing and Finance 11: 355-359.

32. Womack K. L., 1996, *Do brokerage analysts' recommendatons have investment value?* Journal of Finance 51: 137-167.

33. Xia H., 2014, *Can investor-paid credit rating agencies improve the information quality of issuer paid-rating agencies?* Journal of Financial Economics 111: 450-468.

Table 3.1: Firm Characteristics for IBES, S&P, and EJR

The table provides summary statistics for each of the rating agencies IBES, EJR, and S&P. EJR and S&P ratings are assigned valuers from 1 to 23, where 23 refers to the rating with the lowest probability of default (AAA). IBES recommendations are assigned ratings from 1 to 5, where 1 refers to strong buy recommendation while 5 refers to strong sell recommendation.

	(1) IBES	(2) EJR	(3) S&P
Sample Period	1993-2014	1999-2014	1998-2014
N Firms	1799	2402	4615
N Observations	158511	58583	143950
Average Rating	2.357	13.977	13.623
Average Years Per Firm	9.18	6.25	12.36

Table 3.2: Annual Firm Characteristics

The table provides summary statistics for each of the rating agencies IBES, EJR, and S&P. EJR and S&P ratings are assigned values from 1 to 23, where 23 refers to the rating with the lowest probability of default (AAA). IBES recommendations are assigned ratings from 1 to 5, where 1 refers to strong buy recommendation while 5 refers to strong sell recommendation. Firm characteristics include: investment, cash ratio, leverage, total assets, liabilities, revenue, ebitda, operating income. The sample period goes from 1999 until 2014. The total number of firms is 1150. The total number of observations is 10,922.

Sample Period	1999-2014
N Firms	1150
N Observations	10,922
Years Per Firm	≈ 9.5
S&P Average Rating	14.53 (≈BBB)
EJR Average Rating	14.49 (≈BBB-)
IBES Average Rating	2.43 (≈Hold)
Investment	5.8%
Cash	6.6%
Leverage	13.9%
Total Assets	4.63B
Liabilities	3.82B
Revenue	1.46B
EBITDA	260M
Operating Income	$109M

Table 3.3: Impact of EJR and S&P Rating Changes on Equity Analyst Recommendations

The table evaluates the impact of changes in EJR and S&P ratings on equity analysts' recommendations. The dependent variable $\Delta IBES_{i,t}$ is defined as $IBES_{i,t}$-$IBES_{i,t-1}$. In models (1), we regress $\Delta IBES_{i,t}$ on $\Delta EJR_{i,t-1}$ and $\Delta S\&P_{i,t-1}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in equity analysts' recommendations. Model (3) also incorporates lead changes in EJR and S&P ratings . ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	$\Delta IBES_{i,t} = IBES_{i,t}$-$IBES_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\Delta EJR_{i,t-1}$	-0.0494***	-0.0479***	-0.0479***	
	(0.0175)	(0.0175)	(0.0175)	
$\Delta S\&P_{i,t-1}$	-0.0256	-0.0221	-0.0215	
	(0.0204)	(0.0204)	(0.0204)	
$\Delta EJR_{i,t+1}$			-0.0260	-0.0267
			(0.0176)	(0.0176)
$\Delta S\&P_{i,t+1}$			0.0308	0.0295
			(0.0374)	(0.0374)
$\Delta IBES_{i,t-1}$		-0.0681***	-0.0681***	-0.0682***
		(0.00552)	(0.00552)	(0.00552)
$ROA_{i,t-1}$		-0.0967	-0.0929	-0.0979
		(0.0868)	(0.0868)	(0.0868)
$Size_{i,t-1}$		0.00675	0.00664	0.00691
		(0.00639)	(0.00639)	(0.00639)
$Debt_{i,t-1}$		-0.00100*	-0.00100*	-0.00101*
		(0.000568)	(0.000568)	(0.000568)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.0480	0.0485	0.0445
		(0.149)	(0.149)	(0.149)
$Tangibles_{i,t-1}$		-0.0204	-0.0203	-0.0202
		(0.0426)	(0.0426)	(0.0426)
N	28946	28946	28946	28946
R^2	0.241	0.245	0.245	0.245
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 3.4: Impact of Equity Analysts' and S&P Ratings on Changes in EJR Ratings

The table evaluates the impact of changes in equity analysts and S&P ratings on EJR ratings. The dependent variable $\Delta EJR_{i,t}$ is defined as $EJR_{i,t}$-$EJR_{i,t-1}$. In models (1), we regress $\Delta EJR_{i,t}$ on $\Delta S\&P_{i,t-1}$ and $\Delta IBES_{i,t-1}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in equity analysts' recommendations. Model (3) also incorporates lead changes in IBES and S&P ratings . ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	$\Delta EJR_{i,t} = EJR_{i,t}$-$EJR_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\Delta IBES_{i,t-1}$	0.00137	0.000851	0.000756	
	(0.00306)	(0.00306)	(0.00306)	
$\Delta S\&P_{i,t-1}$	0.0128	0.00958	0.00976	
	(0.0113)	(0.0113)	(0.0113)	
$\Delta IBES_{i,t+1}$			-0.000839	-0.000863
			(0.00291)	(0.00291)
$\Delta S\&P_{i,t+1}$			0.0547***	0.0547***
			(0.0207)	(0.0207)
$\Delta EJR_{i,t-1}$		0.0216**	0.0212**	0.0217**
		(0.00969)	(0.00969)	(0.00967)
$ROA_{i,t-1}$		0.304***	0.302***	0.303***
		(0.0481)	(0.0481)	(0.0481)
$Size_{i,t-1}$		0.0100***	0.00987***	0.00980***
		(0.00354)	(0.00354)	(0.00354)
$Debt_{i,t-1}$		-0.000840***	-0.000833***	-0.000831***
		(0.000315)	(0.000315)	(0.000315)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.206**	0.202**	0.203**
		(0.0827)	(0.0827)	(0.0827)
$Tangibles_{i,t-1}$		0.0107	0.0107	0.0104
		(0.0236)	(0.0236)	(0.0236)
N	28946	28946	28946	28946
R^2	0.041	0.043	0.043	0.043
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 3.5: Impact of Equity Analysts' and EJR Ratings on Changes in S&P Ratings

The table evaluates the impact of changes in equity analysts and EJR ratings on S&P ratings. The dependent variable $\Delta S\&P_{i,t}$ is defined as $S\&P_{i,t}$-$S\&P_{i,t-1}$. In models (1), we regress $\Delta S\&P_{i,t}$ on $\Delta EJR_{i,t-1}$ and $\Delta IBES_{i,t-1}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in equity analysts' recommendations. Model (3) also incorporates lead changes in IBES and EJR ratings . ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	$\Delta S\&P_{i,t} = S\&P_{i,t}$-$S\&P_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\Delta IBES_{i,t-1}$	0.00230**	0.00222**	0.00219**	
	(0.000895)	(0.000895)	(0.000896)	
$\Delta EJR_{i,t-1}$	0.00624**	0.00633**	0.00631**	
	(0.00283)	(0.00283)	(0.00283)	
$\Delta IBES_{i,t+1}$			-0.000230	-0.000252
			(0.000853)	(0.000853)
$\Delta EJR_{i,t+1}$			0.00444	0.00459
			(0.00285)	(0.00285)
$\Delta S\&P_{i,t-1}$		-0.00429	-0.00437	-0.00385
		(0.00331)	(0.00331)	(0.00330)
$ROA_{i,t-1}$		0.0466***	0.0458***	0.0473***
		(0.0141)	(0.0141)	(0.0141)
$Size_{i,t-1}$		0.00244**	0.00244**	0.00240**
		(0.00104)	(0.00104)	(0.00104)
$Debt_{i,t-1}$		-0.0000307	-0.0000298	-0.0000243
		(0.0000921)	(0.0000921)	(0.0000921)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.0737***	0.0733***	0.0732***
		(0.0242)	(0.0242)	(0.0242)
$Tangibles_{i,t-1}$		-0.000936	-0.000956	-0.000819
		(0.00691)	(0.00691)	(0.00691)
N	28946	28946	28946	28946
R^2	0.015	0.016	0.016	0.015
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 3.6: Impact of Changes in Leverage on Equity Analyst Recommendations and Credit Rating Changes

The table evaluates the impact of leverage on equity analysts' recommendations (model 1) and credit ratings (models 2 and 3) in the subsequent quarter. The dependent variable in model (1) is a change in equity analysts' recommendation $\Delta IBES_{i,t}$ $=IBES_{i,t}$-$IBES_{i,t-1}$. The dependent variables in models (2) and (3) are $\Delta EJR_{i,t}$=$EJR_{i,t}$-$EJR_{i,t-1}$ and $\Delta S\&P_{i,t}$=$S\&P_{i,t}$-$S\&P_{i,t-1}$ (respectively). I regress the quarterly changes in the credit ratings and equity recommendations on lagged changes in leverage defined as $\Delta Leverage_{i,t-1}$=$Leverage_{i,t-1}$-$Leverage_{i,t-2}$. All regression specifications include controls for lagged leverage, return on assets, net income. cash over assets, tangible assets, debt, market to book, and sales. I also control for industry and year fixed effects. Standard error are cluster by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	(1) $\Delta IBES_{i,t}$	(2) $\Delta EJR_{i,t}$	(3) $\Delta S\&P_{i,t}$
$\Delta Leverage_{i,t-1}$	-0.886**	-0.521**	0.566
	(0.378)	(0.256)	(0.723)
$Leverage_{i,t-1}$	0.171**	-0.00799	0.0959
	(0.0817)	(0.0987)	(0.0796)
$ROA_{i,t-1}$	0.677***	0.418**	0.104
	(0.220)	(0.175)	(0.0965)
$NetIncome_{i,t-1}$	-0.00297	0.0228**	0.0152*
	(0.00970)	(0.0114)	(0.00773)
$CashOverAssets_{i,t-1}$	0.703*	1.628***	0.203
	(0.376)	(0.398)	(0.165)
$Tangibles_{i,t-1}$	0.00712	-0.0427	-0.0946**
	(0.0789)	(0.0828)	(0.0437)
$Debt_{i,t-1}$	0.000739	-0.00222	0.0000543
	(0.00110)	(0.00164)	(0.00131)
$MarketToBook_{i,t-1}$	-0.0318*	0.0150	0.0283**
	(0.0166)	(0.0185)	(0.0131)
$Sales_{i,t-1}$	0.0169*	-0.00614	-0.0205**
	(0.00968)	(0.0122)	(0.00954)
N	5102	5102	5102
R^2	0.023	0.122	0.055
Industry and Year FE	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes

Table 3.7: Impact of Rating and Equity Analyst Recommendation Changes on Corporate Investment

The table evaluates the impact of rating changes on investment. The dependent variable (investment) is defined as capital expenditure over assets. Models (1)-(3) evaluate the impact of changes in ratings on investment separately for EJR, S&P, and IBES (respectively), while model (4) incorporates all rating changes as independent variables. Firm controls include leverage, revenue, cash flow, as well as rating level coefficients for IBES, EJR, and S&P. The primary coefficients of interest are on the dummy variables for changes in the IBES, EJR, and S&P ratings.Standard errors are clustered by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	$Investment_{i,t}=(\frac{CapitalExpenditure}{Assets})_{i,t}$			
	(1)	(2)	(3)	(4)
$EJR_{i,t-1}^{Upgrade}$	0.00454**			0.00359**
	(0.00185)			(0.00180)
$EJR_{i,t-1}^{Downgrade}$	-0.00616***			-0.00454***
	(0.00146)			(0.00157)
$S\&P_{i,t-1}^{Upgrade}$		0.00431*		0.00257
		(0.00229)		(0.00217)
$S\&P_{i,t-1}^{Downgrade}$		-0.00743***		-0.00486***
		(0.00170)		(0.00188)
$IBES_{i,t-1}^{Upgrade}$			0.00252*	0.00168
			(0.00132)	(0.00131)
$IBES_{i,t-1}^{Downgrade}$			-0.00528***	-0.00434***
			(0.00160)	(0.00161)
$Leverage_{i,t-1}$	0.00411	0.00313	0.00221	0.00581
	(0.0216)	(0.0215)	(0.0217)	(0.0215)
$Revenue_{i,t-1}$	0.00127	0.00132	0.00165	0.00123
	(0.00200)	(0.00199)	(0.00199)	(0.00200)
$Cash_{i,t-1}$	-0.0140	-0.0124	-0.0105	-0.0142
	(0.0151)	(0.0150)	(0.0150)	(0.0150)
$IBES_{i,t-1}$	-0.00431***	-0.00443***	-0.00737***	-0.00597***
	(0.00115)	(0.00116)	(0.00156)	(0.00158)
$S\&P_{i,t-1}$	-0.00370***	-0.00311***	-0.00348***	-0.00340***
	(0.000788)	(0.000787)	(0.000771)	(0.000823)
$EJR_{i,t-1}$	0.00338***	0.00280***	0.00307***	0.00310***
	(0.000678)	(0.000665)	(0.000650)	(0.000707)
N	8875	8875	8875	8875
R^2	0.395	0.395	0.394	0.397
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 3.8: Impact of Upgrade/Downgrade Thresholds on Corporate Investment

The table evaluates the impact of rating changes on investment. The dependent variable (investment) is defined as capital expenditure over assets. Models (1)-(3) evaluate the impact of changes in ratings on investment separately for EJR, S&P, and IBES (respectively), while model (4) incorporates all rating changes as independent variables. Firm controls include leverage, revenue, cash flow, as well as rating level coefficients for IBES, EJR, and S&P. The primary coefficients of interest are on the dummy variables for changes in the IBES, EJR, and S&P ratings.Standard errors are clustered by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	$Investment_{i,t}=(\frac{CapitalExpenditure}{Assets})_{i,t}$		
	(1)	(2)	(3)
$EJR^{Minus}_{i,t-1}$	-0.00183**		-0.00184**
	(0.000861)		(0.000861)
$EJR^{Plus}_{i,t-1}$	-0.00183**		-0.00181**
	(0.000857)		(0.000858)
$S\&P^{Minus}_{i,t-1}$		0.000870	0.000923
		(0.000885)	(0.000885)
$S\&P^{Plus}_{i,t-1}$		-0.000474	-0.000382
		(0.000890)	(0.000891)
$Leverage_{i,t-1}$	-0.0265***	-0.0258***	-0.0262***
	(0.00982)	(0.00982)	(0.00982)
$Revenue_{i,t-1}$	-0.00397***	-0.00391***	-0.00397***
	(0.00121)	(0.00122)	(0.00122)
$Liabilities_{i,t-1}$	0.00969	0.00945	0.00955
	(0.00649)	(0.00649)	(0.00649)
$Cash_{i,t-1}$	0.00670	0.00657	0.00677
	(0.00618)	(0.00618)	(0.00618)
$S\&P_{i,t-1}$	-0.00107***	-0.00103***	-0.00106***
	(0.000254)	(0.000254)	(0.000254)
$EJR_{i,t-1}$	0.00162***	0.00158***	0.00163***
	(0.000222)	(0.000221)	(0.000222)
N	7022	7022	7022
R^2	0.607	0.607	0.607
Industry and Year FE	Yes	Yes	Yes

Table 3.9: Impact of Rating Changes on Excess Returns

The table evaluates the impact of rating changes on excess equity returns. The dependent variable (excess returns) is defined as $Return_{i,t}$-$S\&P500_{i,t}$. Models (1),(2) evaluate the impact of changes in IBES recommendations on equity excess returns. Similarly, models (3),(4) and (5),(6) evaluate the impact of changes in EJR and S&P ratings (respectively) on equity excess returns. Panel A includes data for all firms while Panel B includes data for firms with median S&P ratings below investment grade. Models (1),(3),(5) include controls for rating levels of IBES, EJR, and S&P. Models (2),(4),(6) also include firm controls such as leverage, return on assets, market to book, in addition to rating level coefficients for IBES, EJR, and S&P. For each regression, we create a time window of [-60,+60] days prior and following a rating changes. This time window ensures that during this time frame only one of the ratings changes while the others remained constant. Results in this table include data for all firms in the data. Standard errors are clustered by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Panel A: Impact of Rating Changes on Excess Return - All Firms
Dependent Variable: $Return_{i,t}$-$S\&P500_{i,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$IBES_{i,t}^{Downgrade}$	-0.0363***	-0.164**				
	(0.0106)	(0.0707)				
$IBES_{i,t}^{Upgrade}$	0.0398***	0.167**				
	(0.0114)	(0.0724)				
$EJR_{i,t}^{Downgrade}$			-0.00300***	-0.00411***		
			(0.000979)	(0.00138)		
$EJR_{i,t}^{Upgrade}$			-0.00139	-0.000639		
			(0.00161)	(0.00222)		
$S\&P_{i,t}^{Downgrade}$					0.00130	0.00174
					(0.00117)	(0.00133)
$S\&P_{i,t}^{Upgrade}$					-0.00171	-0.000858
					(0.00334)	(0.00300)
N	1386	1265	2921	2821	3310	3305
R^2	0.015	0.020	0.018	0.017	0.011	0.012
Firm Controls	No	Yes	No	Yes	No	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Impact of Rating Changes on Excess Return-
Firms with Median S&P Rating below Investment Grade
Dependent Variable: $Return_{i,t}$-$S\&P500_{i,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$IBES_{i,t}^{Downgrade}$	-0.00328	0.00791				
	(0.00220)	(0.0296)				
$IBES_{i,t}^{Upgrade}$	0.00417	-0.00853				
	(0.00335)	(0.0284)				
$EJR_{i,t}^{Downgrade}$			-0.00457**	-0.0159***		
			(0.00206)	(0.00528)		
$EJR_{i,t}^{Upgrade}$			0.00330**	0.0138***		
			(0.00145)	(0.00476)		
$S\&P_{i,t}^{Downgrade}$					0.00328	0.00262
					(0.00240)	(0.00252)
$S\&P_{i,t}^{Upgrade}$					0.000244	-0.000353
					(0.00364)	(0.00361)
N	502	419	1356	1356	2112	2108
R^2	0.023	0.035	0.026	0.028	0.006	0.006
Firm Controls	No	Yes	No	Yes	No	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.10: Bond Market Response to Credit Rating and Recommendation Changes

Panels A, B, and C show results for OLS regressions of Log(Spread) on rating changes, upgrades and downgrades, from EJR and S&P, equity analysts' recommendations from IBES,firm specific controls and bond specific controls. Panel A includes data for all firms. Panels B includes data for firms with S&P ratings below investment grade, while Panel C includes data for firms with S&P ratings that cross the investment grade. The bond spread is defined as the difference between the security yield and the treasury yield. Security yields and treasury yields are matched by maturity and coupons. Firm specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, S&P and EJR rating levels, IBES recommendations. All the control variables are one period lagged and winsorized at the 1% level. Regressions (1) and (2) show the effect of EJR rating changes on the bond spread. Regressions (3) and (4) show the effect of IBES equity recommendations on the bond spread. Regressions (5) and (6) show the effect of S&P rating changes on the bond spread. Regressions (7) and (8) show the effect of all the rating changes and equity recommendations on the bond spread. Regressions (2), (4), (6) and (8) add firm and bond specific controls. Regressions (1)-(8) account for year and industry fixed effets. The results refer to the entire sample. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Panel A: All Firms

Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EJR_{i,t}^{Upgrade}$	-0.0270***	-0.0287***					-0.0320***	-0.0349***
	(0.00960)	(0.0107)					(0.0113)	(0.0126)
$EJR_{i,t}^{Downgrade}$	0.150**	0.154**					0.152**	0.153**
	(0.0642)	(0.0631)					(0.0772)	(0.0747)
$IBES_{i,t}^{Upgrade}$			0.00488	0.00735			-0.00300	-0.000598
			(0.00724)	(0.00652)			(0.00727)	(0.00772)
$IBES_{i,t}^{Downgrade}$			0.0162	0.0219***			0.0142	0.0203**
			(0.0101)	(0.00843)			(0.00991)	(0.00864)
$S\&P_{i,t}^{Upgrade}$					0.0253	0.0130	0.0250	0.0118
					(0.0221)	(0.0237)	(0.0241)	(0.0257)
$S\&P_{i,t}^{Downgrade}$					0.0677***	0.0764***	-0.0129	-0.00518
					(0.0155)	(0.0169)	(0.0570)	(0.0512)
N	29977	29977	29977	29977	29977	29977	29977	29977
R^2	0.626	0.642	0.622	0.638	0.622	0.638	0.626	0.642
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Firms with S&P Ratings Below Investment Grade
Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EJR_{i,t}^{Upgrade}$	-0.0293*	-0.0286*					-0.0281	-0.0284*
	(0.0168)	(0.0160)					(0.0172)	(0.0164)
$EJR_{i,t}^{Downgrade}$	0.0683***	0.0704***					0.0547***	0.0547***
	(0.0210)	(0.0211)					(0.0207)	(0.0206)
$IBES_{i,t}^{Upgrade}$			0.0148	0.0165			0.0121	0.0140
			(0.0131)	(0.0127)			(0.0130)	(0.0127)
$IBES_{i,t}^{Downgrade}$			0.00376	0.0121			0.00248	0.0111
			(0.0106)	(0.0101)			(0.0105)	(0.00991)
$S\&P_{i,t}^{Upgrade}$					-0.0270	-0.0318	-0.0262	-0.0327
					(0.0221)	(0.0213)	(0.0234)	(0.0228)
$S\&P_{i,t}^{Downgrade}$					0.100***	0.105***	0.0770***	0.0810***
					(0.0279)	(0.0273)	(0.0270)	(0.0258)
N	8398	8398	8398	8398	8398	8398	8398	8398
R^2	0.620	0.629	0.619	0.628	0.620	0.629	0.620	0.630
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Firms with S&P Ratings that Cross the Investment Grade
Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EJR_{i,t}^{Upgrade}$	-0.0369**	-0.0305**					-0.0357**	-0.0308**
	(0.0155)	(0.0153)					(0.0157)	(0.0155)
$EJR_{i,t}^{Downgrade}$	0.0709***	0.0789***					0.0646***	0.0722***
	(0.0186)	(0.0182)					(0.0183)	(0.0179)
$IBES_{i,t}^{Upgrade}$			0.00390	0.0116			0.00102	0.00869
			(0.0125)	(0.0120)			(0.0124)	(0.0119)
$IBES_{i,t}^{Downgrade}$			0.00148	0.0150			0.000560	0.0138
			(0.0102)	(0.00986)			(0.0104)	(0.00995)
$S\&P_{i,t}^{Upgrade}$					-0.0206	-0.0254	-0.0151	-0.0243
					(0.0201)	(0.0191)	(0.0211)	(0.0206)
$S\&P_{i,t}^{Downgrade}$					0.0644***	0.0597**	0.0376*	0.0285
					(0.0237)	(0.0233)	(0.0224)	(0.0223)
N	11530	11530	11530	11530	11530	11530	11530	11530
R^2	0.636	0.650	0.635	0.649	0.635	0.649	0.636	0.650
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes