The Impact of Increased Credit Rating Quality on Rated Firms

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Doctor of Philosophy

April 2020

Department of Accounting, Faculty of Business and Economics

The University of Melbourne

Submitted in partial fulfillment of the requirements of the degree of

Doctor of Philosophy

Abstract

Following the subprime mortgage crisis of 2007-2008, credit rating agencies (CRAs) faced scathing criticisms from the media and regulators for their role in the unfolding of the Global Financial Crisis (FC). The ensuing reputational damage and the changes to the regulation of CRAs led them to make numerous changes to their rating standards. Several prior studies have since examined the impact of these changes on rating quality, documenting tighter rating standards, lower ratings, and a change in rating quality after the FC. Despite these findings, however, little is understood about how a change in rating quality affects rated firms, and how firms respond to such a change. Using the tightening of rating standards in the wake of the FC as the main setting, this thesis seeks to explore these questions.

Given the private lenders' frequent use of ratings in performance pricing provisions and setting interest rates, the first study explores the changes in two dimensions of debt contracting: the use of rating-based performance pricing provisions, also called rating triggers, and loan spreads. Results suggest that the decline in the use of rating triggers in the post-FC period as documented in deHaan (2017) is muted in cases where the increase in rating quality was likely to be high, and is stronger in loans originated by lenders that had high reputational concerns. Closer inspection of pricing grids reveals that, consistent with lenders perceiving ratings to be more informative after the FC, rating downgrades/upgrades move loan spreads to a greater extent in the post-FC period. Evidence from tests on initial loan spreads provides support to this finding, but is generally weaker. These findings contribute to our understanding of how an increase in rating quality affects rated firms through its impact on debt contracting.

That higher rating quality is associated with more likely downgrades suggests that firms have incentives to respond to an increase in rating quality due to the importance of ratings for firms' debt policy. Accordingly, in light of the theoretical guidance and related empirical evidence, the second study examines whether rated firms increase misreporting in response to an increase in rating quality. In empirical tests, I find that accrual-based earnings management increased in rated firms in the post-FC period, and that this increase was driven by firms with rating triggers. In tests motivated by the CRAs' adjustments to firms' earnings, I also find that firms facing stronger CRA monitoring managed financial numbers that feed into these adjustments to a greater extent in the post-FC period. Considering the information used by CRAs in the rating process comes primarily from financial statements, this study informs regulators regarding the unintended consequences of regulatory reforms that aim to improve overall rating quality.

The final study continues exploring other dimensions of firms' responses to increased rating quality with an emphasis on real firm decisions. Results from tests examining real earnings management proxies indicate no change in the post-FC period for any of the numerous proxies examined. In tests motivated by the S&P's rating criteria, however, I find that rated firms increased their excess cash holdings to a greater extent than non-rated firms after the FC. Results suggest this effect was stronger for firms placed under negative credit watch. Taken together, these findings expand our understanding of firms' responses to an increase in rating quality by providing evidence on the impact of increased rating quality on real firm decisions.

Declarations

This is to certify that

i. the thesis comprises only my original work towards the Doctor of Philosophy;

ii. due acknowledgment has been made in the text to all material used; and

iii. this thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies, and appendices.

Signature: …….

Sabutay Fatullayev

Acknowledgments

I wish to thank my supervisor, Professor Naomi Soderstrom, for her continued guidance, encouragement, and advice in the preparation of this thesis. Throughout my doctoral journey, Naomi has shown tremendous support not only professionally, but also personally. I would also like to thank her for her patience in thoroughly reading multiple drafts of this thesis and providing feedback on them.

I wish to thank my co-supervisors, Professor Gary Biddle and Doctor Stefan Schantl, and the chair of the supervisory committee, Professor Margareth Abernethy, for their continued guidance and advice. Since the early days of my thesis, Stefan has been very generous with his time whenever I knocked on his door, and very helpful with his insights. Gary's unique way of looking at things has been invaluable in always keeping the big picture in mind. Throughout my Ph.D. studies, Maggie has given me invaluable advice and guidance countless times, and I am confident that all of my Ph.D. colleagues would agree when I say Maggie is one of the most caring and supportive mentors.

I would like to acknowledge the financial support of the University of Melbourne, and the Department of Accounting in particular. This support has included scholarships and fundings to attend doctoral symposiums and conferences, and has contributed greatly to my development. I am grateful to everyone who has provided me with feedback regarding my research, including the current faculty members from the University of Melbourne, Jonathan Jona, Mary Barth, Stephan Hollander, Joseph Piotroski, Katherine Schipper, and Mark Wilson. Special acknowledgment must be made of Sandip Dhole, who provided valuable feedback on some parts of this thesis. I would also like to thank the participants at the University of New South Wales, 2018 AFAANZ Doctoral Symposium, and 2019 EAA Doctoral Colloquium. It has been a pleasure to study alongside my Ph.D.

colleagues, namely Hrishikesh Desai, Kerui Zhai, Ajanee Rhanasinghe, Ra-Pee Pattanapanyasat, Chris Stewart, Yunhe Dong, Xing Yang, Mark Wallis, Shaffique Aljoofri, Feilian Wang, Jingru Gao, James Kavourakis, Yanhua Dong, Junyoung Jeong, and Kevin Li.

Finally, and most importantly, I would like to express my sincerest gratitude to my beloved parents, Hikmat and Esmira, and my wife, Deniz. This journey would not have been possible if it was not for the continuous support and encouragement I received from my parents, and the efforts and hardships they went through to provide their children with the highest education and the opportunity to pursue what they love most. This thesis would perhaps not be complete in time if it was not for Deniz's continued care and support, especially when my health problems towards the end of this journey made the finish line look all the more difficult to cross. Finally, I would like to sincerely thank my friends, both here and in Azerbaijan, who have been there whenever I needed their help most.

TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

Chapter 3

Chapter 4

Chapter 5

Chapter 1

Introduction

In the wake of the Global Financial Crisis (FC) beginning in 2008, credit rating agencies (CRAs) became the subject of intense regulatory and public scrutiny following revelations of lax rating standards leading to the subprime mortgage crisis. The resulting reputational damage led to reduced reliance on ratings by not only the investors in complex financial instruments but also the traditional bond investors and lenders (CFA Institute, 2014; deHaan, 2017; Jaballah, 2015). To restore their reputation and satisfy the new regulatory requirements, CRAs responded by making numerous changes to their rating methodologies, improving the transparency around their rating criteria, and implementing new procedures to better monitor conflicts of interest (SEC, 2011).

Findings from prior research suggest that these changes led to significantly lower rating inflation and lower ratings, with the majority of studies also documenting increased rating quality after the FC (see Chapter 2 for more details).[1] Importantly, due to the prevalence of rating inflation across all rating products, many changes made to rating standards and methodologies applied to not only the ratings assigned to structured finance products but also the issuer ratings and corporate bond ratings. As a result, rating quality was affected across all rating classes, including bond ratings (as can be inferred from the findings of studies on bond rating quality).

[1] Throughout the thesis, I frequently refer to the collection of changes implemented by CRAs in the wake of the FC – regardless of whether they were voluntary or required by law – as the tightening of rating standards due to the nature of these changes. If necessary, such labelling also allows for a more neutral discussion about the changes made during this time period without making assumptions regarding their impact on rating quality or a directional change in rating quality.

Despite extensive prior research on how the changes in rating standards affected rating quality, however, little is understood about the consequences for firms of a change in rating quality and firms' response to it. This thesis seeks to explore these research questions. As a result, and in contrast to prior studies, it focuses on the impact of tightening rating standards and changes in rating methodologies in the wake of the FC on rated firms, and firms' responses to these changes. Taking into account the findings from prior studies, I start the thesis by only assuming tighter rating standards after the FC without making further assumptions about the direction of the change in rating quality when developing hypotheses. This assumption is updated in later parts of the thesis in light of the results from initial tests.

The thesis comprises six chapters. The remainder of Chapter 1 provides a summary of the main results and insights from each of the three studies, which are presented in Chapters 3-5. Chapter 2 provides a detailed discussion of the institutional setting. Chapter 3 investigates the changes in debt contracting when rating quality changes. Chapter 4 examines whether the rated firms' reporting quality changes in response to an increase in rating quality. Chapter 5 explores the changes in rated firms' real activities management and liquidity in response to an increase in rating quality. Chapter 6 concludes.

1.1 Rating quality and debt contracting

Credit ratings are important determinants of loan spreads and are commonly used by private lenders (hereafter, lenders) in debt covenants and performance pricing (PP) provisions (Asquith, Beatty, & Weber, 2005; deHaan, 2017).[2] Debt contracting is hence one of the major channels through which a change in rating quality is expected to affect

[2] Performance pricing provisions tie the loan spread to the firm's credit rating (usually, senior debt rating) and cause the interest rate on a loan to automatically change with rating movements.

rated firms. Since a change in rating quality implies a change in the precision of information conveyed through ratings, it is likely to have an impact on how often lenders rely on ratings in debt contracts and how strongly loan spreads move in response to rating movements. Consequently, Chapter 3 examines the extent to which the tightening of rating standards after the FC affected the use of ratings in debt contracts and loan spreads.[3] Rating-based PP provisions (also called "rating triggers") provide a unique setting to address the study's research question because in these contract provisions the borrower's credit rating is tied to the loan spread, allowing for tests to isolate the impact of an increase in rating quality from other effects borne out of reputational damage to rating agencies.[4]

Chapter 3 builds on the findings of deHaan (2017), who finds that corporate credit rating performance improved after the FC while lenders reduced their reliance on ratings in PP provisions. He attributes this finding to CRAs suffering from reputational damage due to their inaccurate ratings assigned to complex financial instruments before the FC. Results from Chapter 3 provide some support to this presumption: investment banks, which faced scathing regulatory and public criticisms during the FC for providing CRAs with incentives to inflate ratings (Story, 2010), reduced the use of rating triggers to a greater extent than other banks. Importantly, a battery of empirical tests provides consistent evidence suggesting that the increase in rating quality in the wake of the FC was an important factor contributing to lenders' decisions of which loan contracts would include a rating trigger. Specifically, despite the reputational costs of relying on ratings,

[3] Throughout the thesis, unless stated otherwise, the FC period refers to the period spanning years 2008 and 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively.
[4] Note that rating-based PP provisions are different from rating-based debt covenants, even though CRAs often use "rating triggers" as an umbrella term for both. For example, some contracts include covenants that require a borrower to post collateral if the borrower's rating falls below investment grade, while others, in a more extreme scenario, require the acceleration of loan repayment. Prior empirical studies have so far exclusively focused on the former when examining the use of ratings in debt contracts, primarily due to the unavailability of data on rating-based debt covenants. Following prior literature, I examine PP provisions for purposes of hypothesis development and testing and refer to them as rating triggers for simplicity.

lenders retained their use of rating triggers in cases where the increase in rating informativeness was likely to be high, and reduced their rating usage in other cases.

A change in rating quality may affect a borrower's cost of debt in two ways: through the initial interest charged on loans, and through the changes in future loan spreads that are predetermined in performance pricing grids.[5] Since pricing grids specify the loan spread for each credit rating in advance, a change from one period to another in the extent to which the loan spread moves when the borrower's rating is upgraded/downgraded is likely to reflect the lender's opinion of whether ratings have become more informative.[6] Consistent with more informative ratings in the post-FC period, results indicate a one-notch decrease (increase) in a credit rating leads to, on average, a 15 basis point increase (12 basis point decrease) in loan spreads in the pre-FC period but a 22 basis point increase (20 basis point decrease) in the post-FC period. There is also some evidence from tests on initial interest rates suggesting that borrowers that likely experienced a bigger increase in CRA monitoring in the post-FC period received larger discounts when the PP provisions relied on ratings rather than other performance metrics.

Chapter 3 contributes to the rating quality literature by documenting changes in different dimensions of debt contracting in response to higher rating quality. The findings on the use of rating triggers complement those of deHaan (2017) by expanding our knowledge about lenders' reactions to the changes in rating standards after the FC. The results concerning the impact of rating quality on initial loan spreads provide support to those documented in Badoer, Demiroglu, and James (2019), who find that bond yields increase when the borrower's issuer-paid rating is higher than its investor-paid rating.

[5] Pricing grid is a table that details how the loan spread changes vis-à-vis borrower's financial performance, which is predominantly measured by credit ratings or accounting ratios.
[6] See Appendix C of Chapter 3 for an example of a pricing grid, and subsection 3.5.2 for a detailed examination of the structure of pricing grids.

Unlike Badoer et al. (2019), Chapter 3 focuses on the use of rating triggers and the pricing of loans with such provisions, thus expanding the stream of literature that examines the use of PP provisions. Moreover, based on a detailed analysis of pricing grids, Chapter 3 provides evidence that rating quality affects not only the initial loan spreads but also expected loan spreads as firm's credit ratings change in the future. To the best of my knowledge, this is the first study to investigate the structure of pricing grids in detail, and to document how lenders incorporate a change in information quality into pricing grids.

1.2 Rating quality and firms' reporting quality

Prior research finds that rating movements induce a significant reaction from equity and public debt investors as well as from lenders, suggesting that ratings provide markets with incremental information about firms' credit quality (Hand, Holthausen, & Leftwich, 1992; Tang, 2009). Therefore, an improvement in rating quality is expected to increase the extent to which not only interest rates but also bond and equity prices respond to rating downgrades and upgrades (e.g., Jankowitsch, Ottonello, and Subrahmanyam (2017)). Such changes in the strength of market reactions are likely to provide firms with stronger incentives to influence their ratings to avoid the potential downgrades that may result from lower rating inflation. In light of the theoretical studies examining the impact of rating inflation and CRA monitoring on firms' misreporting behavior (Cohn, Rajan, & Strobl, 2018; Lee & Schantl, 2019), Chapter 4 explores the changes in rated firms' reporting quality in response to an increase in rating quality.[7]

In empirical tests, I find that abnormal accruals increased for rated firms from the pre-FC to the post-FC period, while remaining similar for non-rated firms. Results

[7] For empirical evidence on how firms with rating-related incentives engage in accrual-based earnings management, see Alissa, Bonsall, Koharki, and Penn (2013), Liu, Subramanyam, Zhang, and Shi (2018), and Jung, Soderstrom, and Yang (2013).

indicate this increase is driven by firms with rating triggers, which is consistent with the findings from Chapter 3 that rating movements have bigger cost of debt implications for these firms in the post-FC period. These findings are robust to controlling for possibly different credit quality of rated and non-rated firms in the post-FC period arising from a change in the borrowing environment (McKinsey & Co., 2018).

To increase the robustness of results, I also develop an earnings management (EM) proxy that is motivated by the CRAs' adjustments to operating income during the rating process. This metric is intended to capture rated firms' attempts to boost a measure of earnings important for the rating assessment by managing the specific financial numbers that feed into these adjustments (see subsection 4.3.3 for more details). One advantage of using this measure over more traditional accrual-based EM proxies is that it comprises financial numbers (predominantly accruals) that are important for the rating process, and hence, results can be more readily attributed to a change in rating quality. This way of influencing ratings is also arguably harder to detect because the adjustment process involves a long list of financial numbers, so even small changes to these numbers may accumulate and have a material impact on the rating assessment.

Results from tests using this EM proxy lend support to preliminary results documented in abnormal accruals tests. Moreover, consistent with the argument that it is harder to detect, the increase in rating adjustments-motivated EM was stronger for firms facing strong CRA monitoring and due diligence (i.e., firms at the investment grade threshold or firms with minus-notch ratings).[8] Taken together, results from Chapter 4 suggest that rated firms are likely to increase misreporting when CRAs tighten their rating standards.

[8] Minus-notch ratings are ratings at the lower end of each rating category (e.g. AA-, A-, BBB- etc).

Chapter 4 contributes to the rating quality literature by examining the change in rating quality from the firms' perspective, as opposed to prior studies that have so far focused on the impact of regulatory changes and reputational shocks on CRAs' behavior. Since the quality of information used in the rating process significantly affects rating quality, an important implication of the findings documented in Chapter 4 is that when rating standards improve, the increase in overall rating quality may at least in part be offset by a decline in rated firms' reporting quality. Consequently, Chapter 4 informs regulators on the unintended consequences of regulatory changes that aim to improve overall rating quality. Additionally, it highlights a previously unexplored factor – adjustments to operating income – that may be used by firms to get a positive rating assessment from CRAs and develops a metric that captures these adjustments using publicly available data.

1.3 Rating quality and real firm decisions

Having established that an increase in rating quality impacts rated firms' reporting quality, in Chapter 5 I proceed to examine other dimensions of firms' responses to an increase in rating quality. The first set of tests focuses on whether tighter rating standards prompted rated firms to manage real activities, because accrual-based EM alone might not have been sufficient to maintain the firm's desired rating. What differentiates the setting examined in this thesis from those used in prior real EM studies is that managing operating activities to influence the firm's rating may be a risky strategy due to its potentially negative impact on the firm's future cash flows. Considering the importance of future cash flows for the firm's ability to pay off its obligations, engaging in real EM to achieve higher earnings may instead result in a negative rating assessment from CRAs if it negatively affects future profitability. Consistent with this argument, results indicate

that there was no significant change in rated firms' real activities management from the pre-FC to the post-FC period.

Motivated by the CRAs' rating criteria, the second set of tests investigates whether the increase in rating quality had an impact on firms' financial risk. For this test, I focus on liquidity because liquidity analysis has become an increasingly important part of the CRAs' financial risk assessment after the FC (S&P, 2008c). Moreover, since companies with higher cash surplus are able to pay back their obligations more easily even during difficult times, surplus cash – an important component of liquidity – is deducted from debt when calculating financial ratios for the purposes rating assessment (S&P, 2013b). Using the Opler, Pinkowitz, Stulz, and Williamson (1999) measure of excess cash as a proxy for liquidity, I find an increase in excess cash in the post-FC period that is higher for rated firms than for non-rated firms. Additionally, results suggest that after the FC rated firms increase their excess cash to a greater extent when placed under negative credit watch. Although credit watches are usually resolved within a few months of their initiation, managers can signal their intention of increasing liquidity to avoid a downgrade once the credit watch resolves.

The findings from Chapter 5 contribute to our understanding of how firms respond to an increase in rating quality in two ways. First, it provides evidence that suggests firms are unlikely to engage in real EM in response to an increase in rating quality, possibly because of its potentially negative impact on their future cash flows. Second, to the best of my knowledge, it is the first study to document firms increasing their liquidity due to rating-related incentives. An important implication of this finding is that an increase in rating quality may impact not just a firm's reporting quality, but also real firm decisions that influence credit policy.

Chapter 2

Institutional Setting

2.1 Credit rating quality before the Global Financial Crisis

A credit rating is a relative measure of an individual obligation's or an obligor's creditworthiness. Since investors lack sufficient time to evaluate all necessary information before making an investment decision, they rely on ratings for an assessment of the issue's creditworthiness (NRSRO Monitoring Unit, 2014). Consequently, when CRAs are given incentives to assign optimistically biased ratings to issues with high underlying credit risk, the result is the gradual increase in the number of highly-rated low-quality issues in the market. The rapid growth of the asset-backed securities market in the early 2000s provided CRAs with such incentives as rating agencies were battling to gain a larger share of the growing rating market (He, Qian, & Strahan, 2011). Many CRA analysts and executives were aware of the unsustainable nature of such practices, but either turned a blind eye with the fear of losing lucrative deals to competitors or were "encouraged to remain silent" when they voiced concerns (Neate, 2011; SEC, 2011). As ratings failed to provide investors with a timely warning of an impending market collapse, the subprime mortgage crisis of 2007-2008 caught many investors unprepared and resulted in significant losses (Lucchetti & Ng, 2007).

Revelations of lax rating standards leading to the subprime mortgage crisis brought renewed attention to the importance of rating quality and damaged CRAs' reputation as providers of objective risk assessment. In a 2011 report, the Securities and Exchange Commission (SEC) criticized CRAs for frequent breaches of rating methodologies, failing to provide timely disclosures and corrections of errors during the rating process, and leaking information about future rating movements, among other problems

(Eaglesham & Neumann, 2011; Hilzenrath, 2011; SEC, 2011).[9] As the global financial crisis unfolded, CRAs also came under scathing criticism from lawmakers and the media for fueling the crisis.[10] Evidence indicates the market reaction to rating movements became significantly weaker as the official inquiries into CRAs' rating processes revealed material deficiencies (Bedendo, Cathcart, El-Jahel, & Evans, 2013; Han, Pagano, & Shin, 2012; Jaballah, 2015). These findings are consistent with the survey results that investors are more cautious in using ratings as guidance in investment decisions after the FC (CFA Institute, 2014).

Regulators and academics agree that the main driver of rating inflation is conflicts of interest inherent in the rating process. Conflicts of interest mainly arise from the use of the "issuer-pays" business model and the ability of issuers to "shop" for ratings.[11] The former refers to a business model where the CRA is paid for a rating assessment by the issuers it rates. The latter arises when an issuer buys a rating from a CRA that it considers as having a more lenient rating assessment. These two factors give CRAs incentives to assign inflated ratings to retain clients and generate more revenue. These incentives become especially strong when economic conditions are good, fee income from rating complex securities is high, and investor reliance on ratings is strong (Bar-Isaac & Shapiro, 2013; Bolton et al., 2012; Mathis, McAndrews, & Rochet, 2009). Increased competition among CRAs exacerbates the problem as CRAs become more willing to provide inflated ratings to retain their market share (Becker & Milbourn, 2011; Bolton et al., 2012).

[9] Following the crisis, the U.S. Department of Justice and a number of states filed lawsuits against biggest rating agencies. Consequently, Standard and Poor's (S&P) was charged with a $1.5 billion fine in 2015, and Moody's agreed to pay nearly $864 million in 2017 (Freifeld, 2017; Viswanatha & Freifeld, 2015).

[10] See Lucchetti and Ng (2007), Eaglesham and Neumann (2011) and Podkul and Banerji (2019). The Financial Crisis Inquiry Commission (2011) even conlcuded that "the failures of credit rating agencies were essential cogs in the wheel of financial destruction".

[11] For a theoretical model of how conflicts of interest affect rating quality, see Bolton, Freixas, and Shapiro (2012). For empirical evidence on how "issuer-pays" model may affect rating quality, see Jiang, Stanford, and Xie (2012) and Bonsall IV (2014). For a discussion of how rating shopping works, see Podkul and Banerji (2019).

Empirical evidence suggests that conflicts of interest affect not only the quality of ratings assigned to structured finance products but also the quality of ratings assigned to corporate bonds and issuer ratings (Baghai & Becker, 2018; Becker & Milbourn, 2011; Kronlund, 2019).

Another factor impacting rating quality is the oligopolistic market structure of the rating industry. Three rating agencies (also called the Big Three) – S&P, Moody's, and Fitch Ratings – dominate the rating industry with a combined market share of 95 percent (Alessi, 2015). The high market share of these CRAs can at least partially be attributed to regulations that were in place before the FC. Until very recently, only the ratings of the so-called Nationally Registered Statistical Rating Organizations (NRSRO) could be used for regulatory purposes. Moreover, it was not until 2006 that the regulation allowed smaller agencies to be recognized as NRSROs. This long-running regulatory exclusivity allowed the Big Three to enjoy unchallenged dominance in the credit rating market.

2.2 Changes to the regulation of CRAs and rating standards in the US

An overhaul of regulations concerning CRAs was one of the major goals of the regulatory changes that followed the FC. The most important of these changes was the adoption of the Dodd-Frank Wall Street Reform and Consumer Protection Act (hereafter, Dodd-Frank) in July 2010. The Act not only adopted rules aimed at increasing CRAs' liabilities for issuing inaccurate ratings but also vested the SEC with additional oversight authority over CRAs. Additionally, it delegated the SEC with the responsibility of achieving what the lawmakers saw as two main objectives in coming few years: (1) to develop specific rules to curb conflicts of interest and increase transparency; and (2) to eliminate regulatory reliance on credit ratings.

Acting on the provisions of Dodd-Frank, the SEC drafted a new set of rules to improve the regulatory oversight of CRAs. The proposed rules were published in May 2011 and adopted in August 2014. The main goal of these rules was "to improve the quality of credit ratings and increase credit rating agency accountability" by addressing the conflicts of interest in CRAs' internal control practices and by improving the transparency of credit rating methodologies (SEC, 2014).[12] The new requirements also led to a substantial increase in CRA disclosures. For example, now rating agencies must not only submit annual internal control reports to the SEC, but also disclose all rating methodologies on their websites, inform the public about upcoming changes to existing methodologies to seek public comments, and disclose certain qualitative and quantitative information to accompany each rating action.

Despite significant changes to the regulation of CRAs, some have criticized the SEC for not fully implementing the directives of Dodd-Frank (Partnoy, 2017). First, when Dodd-Frank mandated issuers to ask for CRAs' consent before they could provide credit ratings in their prospectuses, CRAs refused to provide such consent because it would ultimately make them liable for their ratings. Consequently, the new offerings market temporarily stopped functioning, leaving public companies unable to raise capital. This prompted the SEC to issue a "no-action letter" to relieve issuers from seeking such consent, and in the process, relieved CRAs from liability for their ratings, allowing them to bypass one of the key mandates of Dodd-Frank (Carbone, 2010). Second, Regulation Fair Disclosure of 2000 had previously prohibited the disclosure of selective non-public information by firms to equity analysts. Credit analysts had been exempt from this rule until Dodd-Frank repealed this exemption. However, as per the Regulation FD, companies can still provide private information to any party who expressly agrees to

[12] See Appendix for a detailed list of key changes as a result of the regulatory overhaul.

maintain the disclosed information in confidence. Additionally, Regulation FD does not apply to disclosures made to CRAs if the ratings are made publicly available (Carbone, 2010). Since the changes mandated by Dodd-Frank had no effect on the existing practice in either of these cases, critics have argued that the SEC should have taken further steps to fully implement the "will of Congress" (Partnoy, 2017).

Driven by the criticisms, however, CRAs took steps to restore their damaged reputation even before the adoption of Dodd-Frank and the passage of new regulations by the SEC. For example, in 2008, S&P revised its approach to rating non-investment grade credits, citing the migration of ratings downward over the years and a need for more timely information, greater transparency, and enhanced surveillance efforts. In addition, S&P started recognizing credit stability as an important rating factor in 2008, refined and expanded its financial risk/business risk matrix in 2009, and standardized its liquidity descriptors in 2010 along with other changes aimed at improving rating accuracy. In one of its special reports, S&P even stated that it expected negative client reaction due to an increase in "downgrades or the difficulty of getting high ratings on new issues" as a result of tightening rating standards (S&P, 2009). The transparency in communicating rating criteria has also greatly improved: the existing rating criteria are documented in greater detail and updated more frequently since 2008, and the expected changes in rating methodologies are conveyed with greater transparency. Such improvements in rating standards are not limited to S&P, and can be observed for other big CRAs as well.

2.3 Evidence on the change in rating quality after the FC

Several studies have empirically examined whether the changes in rating standards in the wake of the FC had a material impact on rating quality. Dimitrov, Palia, and Tang (2015) find that after the passage of Dodd-Frank, CRAs started issuing lower ratings,

giving more false warnings, and issuing downgrades that were less informative. They attribute these findings to CRAs' reputational concerns, and argue that CRAs became more protective of their reputation and started issuing more conservative ratings. Follow-up studies, however, reach different conclusions. Employing a battery of rating performance tests, deHaan (2017) documents an improvement in the performance of corporate bond ratings – including a decline in the number of false warnings – following the FC. Jankowitsch et al. (2017) provide evidence indicating that secondary bond market reactions to rating movements became stronger after the adoption of Dodd-Frank. Ahmed, Wang, and Xu (2017) find that CRAs started placing more weight on firm fundamentals after the regulatory changes, which in turn helped improve rating quality. Collectively, these findings are consistent with the conclusions of the first SEC report on post-FC CRA performance and the earlier evidence from prior research that suggests CRAs respond positively to regulatory pressure and reputational damage (Cheng & Neamtiu, 2009; SEC, 2011).[13]

A possible reason for the different results from Dimitrov et al. (2015) and the follow-up studies is differences in research designs. Specifically, unlike Dimitrov et al. (2015), the follow-up studies isolate the FC period from the rest of the sample and compare the ratings from the pre-FC period with the ratings after the adoption of Dodd-Frank. Additionally, these studies control for firm and issue characteristics in empirical tests.

Regardless of the different conclusions of prior studies in regard to how rating quality changed after the FC, all studies agree that CRAs took actions that affected the rating process and reduced rating inflation. The set of arguments and discussions from

[13] The SEC report noted that CRAs had made operational improvements and had enhanced their internal control practices following the FC, although some "apparent failures" still existed (SEC, 2011).

Dimitrov et al. (2015) suggest that the tightening of rating standards was more aggressive than the degree of pre-FC rating inflation justified, resulting in overly conservative ratings which were lower but not more accurate or informative than they were before the FC. The other studies, however, argue that the change in rating criteria and increased monitoring reduced rating inflation to the extent that rating accuracy improved. Taking the different views from prior literature into account, in the remainder of this thesis I start by only assuming a change in rating quality and tighter rating standards after the FC without making further assumptions about the direction of the change when developing hypotheses.[14] I update this assumption (for hypothesis development) in later parts of the thesis taking into account the inferences from initial tests.

[14] Alp (2013) and Baghai, Servaes, and Tamayo (2014) find that rating standards have been tightening for the last few decades. Since their sample periods end before the FC, however, it is not clear how that trend changed during or after the FC. Consequently, based on the evidence discussed in this Chapter, this thesis assumes that during the FC there was a structural break in the speed at which rating standards had been tightening.

Appendix: *Main regulatory changes adopted by the SEC concerning CRAs*

Proposed in 2011 and adopted in 2014, the new rules and amendments, which implement 14 rulemaking requirements under Dodd-Frank, apply to credit rating agencies registered with the SEC as NRSROs. Below are the highlights of the amendments and new rules as they appear in a report published by SEC (2014):

1) NRSROs are required to establish, maintain, enforce, and document an effective internal control structure governing the implementation of and adherence to policies, procedures, and methodologies for determining credit ratings, taking into consideration such factors as the Commission may prescribe, by rule.

2) NRSROs are required to annually submit to the Commission an internal controls report that contains information on management's responsibilities relating to the internal control structure, the effectiveness of the internal control structure, and an attestation of the CEO or equivalent on the report.

3) To address the conflicts of interest: a person that participates in the preparation of a rating cannot also participate in sales or marketing roles of the product. Exceptions can be provided for small NRSROs.

4) NRSROs should periodically conduct a "look-back" review to determine whether the prospect of future employment by an issuer or underwriter influenced a credit analyst in determining a credit rating, and, if such influence is discovered, to revise the credit rating in accordance with rules the Commission shall prescribe.

5) NRSROs are required to publicly disclose information about their initial credit ratings and subsequent changes to the credit ratings to allow users of credit ratings to evaluate the accuracy and compare the performance of credit ratings across NRSROs.

6) Certain new rules are prescribed regarding NRSROs' use and implementation of credit rating methodologies. All rating methodologies the NRSROs use should be made publicly available. All procedures and methodologies the NRSROs use to determine the credit ratings must be approved by their board. When there is a material change to these procedures or methodologies, the change should be applied consistently to all current and future credit ratings to which the changed procedures or methodologies apply. In such cases, the NRSRO should promptly publish any material changes to the credit rating methodologies and the reason for it (also in case there was an error in determining a specific credit rating).

7) The SEC's rule amendments require an NRSRO to publish two items when taking certain rating actions: a form containing the quantitative and qualitative information about the credit rating specified in the statute, and any certification of a provider of third-party due diligence services received by the NRSRO that relates to the credit rating.

8) The issuer or underwriter of an asset-backed security should make publicly available the findings and conclusions of any third-party due diligence report obtained by the issuer or underwriter.

9) Third-party due diligence services for asset-backed securities should provide a written certification to any NRSRO that produces a credit rating to which the services relate and provides that the Commission shall establish the format and content of the written certification.

10) SEC has issued a number of rules requiring NRSROs to constantly check the quality of its analysts and products, and if necessary, to provide proper punishment or training to its staff responsible for credit ratings.

Chapter 3

Rating quality and debt contracting

Abstract

Prior research finds that, following the FC, lenders reduced their reliance on ratings in debt contracts due to the damage to CRAs' reputation. In this chapter, I argue that after the FC, lenders became more selective concerning which loan contracts would include a rating trigger based on the trade-off between reputational costs of relying on ratings and benefits gained from increased rating informativeness. Consistent with this argument, results indicate lenders decreased their use of rating triggers when the reliance on ratings had high reputational costs, but retained their use of rating triggers in cases where rating quality likely improved to a greater extent. Results from tests on loan spreads suggest that consistent with increased rating quality affecting loan spreads, the impact of rating movements on loan spreads became stronger in the post-FC period as reflected in pricing grids. There is also some evidence suggesting borrowers that likely experienced a greater increase in CRA monitoring in the post-FC period received lower initial interest rates if the loan contract included a rating trigger. These findings contribute to our understanding of how an increase in rating quality affects different dimensions of debt contracting, and consequently, rated firms.

3.1 Introduction

A firm's credit rating is one of the two most important factors affecting its debt policy due to lenders' and public debt investors' strong reliance on ratings (Graham & Harvey, 2001). Lenders frequently use ratings in setting interest rates, debt covenants, and performance pricing provisions. Since a change in rating quality implies a change in the level and the precision of ratings, it is likely to affect loan spreads as well as various terms of loan contracts. That lenders are among the most frequent users of ratings thus makes debt contracting one of the most important channels through which a change in rating quality is expected to affect rated firms. Using performance-sensitive debt as the main setting, this chapter examines the impact of a change in rating quality on the use of ratings in debt contracts and loan spreads.[15] This setting is well-suited for addressing the study's research question because in performance-sensitive debt contracts that rely on rating-based PP provisions loan spreads are directly tied to the borrower's credit rating, thus strengthening the association between cost of borrowing and rating quality. The availability of data on the structure of pricing grids also allows for cleaner tests to gauge the direction, and isolate the impact, of a change in rating quality.

In a study that examines the performance of ratings after the FC, deHaan (2017) documents a decline in lenders' use of rating triggers along with an improvement in rating quality. He also finds that the use of rating triggers did not recover at least within the three years after the FC, therefore concluding the damage to the reputation of CRAs deterred lenders from relying on ratings despite higher rating quality. If rating quality did improve after the FC, it is likely that lenders, faced with more informative ratings but higher reputational costs of using them in contracts, became more selective regarding which loan

[15] Performance-sensitive debt refers to debt contracts that include PP provisions.

contracts would include a rating trigger. Where the benefits gained from increased rating informativeness would exceed the reputational costs of relying on ratings, lenders might have *retained* or *increased* their use of rating triggers. Consequently, if the changes in rating standards in the wake of the FC translated into more informative ratings, I expect the decrease in the use of rating triggers to be either muted or reversed in loans provided to firms that likely faced a greater increase in CRA monitoring following the FC.[16]

Since deHaan (2017) does not formally test whether the decline in the use of rating triggers was due to the reputational damage to ratings, I start the empirical analysis by testing this presumption. For the purposes of this test, I examine whether this decline was stronger in loans originated by systemically important financial institutions and investment banks.[17] Although Dodd-Frank brought about many new requirements for all banks, the monitoring of systemically important financial institutions received greater attention due to their role in the unfolding of the FC (more details provided in section 3.3). Despite not being subjected to the same level of regulatory scrutiny, investment banks faced even greater public criticisms for providing CRAs with incentives to inflate ratings (Story, 2010). These banks were hence likely to be more reluctant to rely on ratings in the post-FC period given their reputational concerns and/or the intense regulatory scrutiny they faced. Results from tests performed on these subsamples of banks provide some support for the reputational costs argument. Specifically, the decline in the use of rating triggers was stronger in loans originated by investment banks, but was not significantly different between systemically important institutions and other banks.

[16] An implicit assumption behind this prediction is that tighter CRA monitoring/scruitny of firms increases the informativeness and reliability of ratings assigned to these firms.
[17] The list of systemically important financial institutions include Bank of America, Bank of New York Mellon, Citigroup, Wells Fargo, Goldman Sachs, Morgan Stanley, JP Morgan Chase, and State Street (Financial Stability Board, 2011).

To investigate the extent to which a potential increase in rating informativeness after the FC affected the use of ratings in PP provisions, I first partition the sample based on the Z-score of borrowers with the same issuer rating (Altman, 2000). The rationale behind this partitioning is that the CRA monitoring of borrowers with a similar rating but weaker fundamentals is likely to tighten to a greater extent in the post-FC period, because the lack of timeliness was one of the most heavily criticized aspects of ratings during the FC. Second, I partition the sample based on whether the firm has a high concentration of public debt in its capital structure. Ratings are arguably more important for public debt investors, and thus, CRAs' monitoring of firms that borrow predominantly from public investors likely improved to a greater extent following the criticisms of CRAs.[18] Consistent with lenders using the increase in rating informativeness as a factor in deciding which loan contracts would include a rating trigger, I find that the use of rating triggers remained unchanged in loans provided to firms that experienced a bigger increase in CRA monitoring in the post-FC period, but decreased in loans provided to other borrowers. Subsample analyses based on debt structure complexity yield similar inferences (see subsection 3.6.2 for more details).

The frequency with which ratings are used in debt contracts is not the only dimension of debt contracting likely to be affected by a change in rating quality. An equally and arguably more direct channel through which rating quality is expected to affect rated firms is loan spreads. A change in rating quality may affect loan spreads in two ways: through initial interest rates charged on loans, and through future changes in loan spreads when the borrower's financial performance deteriorates/improves (i.e.,

[18] Unlike banks, who have access to more detailed information about their borrowers, public investors have to rely more on rating agencies in assessing the creditworthiness of borrowers. In fact, much of public criticisms directed at CRAs during the crisis revolved around low quality ratings misleading public investors who over-relied on them.

through pricing grids). Prior research finds that when downgrades are more likely, borrowers are rewarded with lower initial interest rates because more likely downgrades imply higher future costs for the borrower, especially when ratings are directly tied to the loan spread (e.g., Asquith et al., 2005). Since tightening rating standards led to more likely downgrades and an increase in the difficulty of getting a high rating after the FC (deHaan, 2017; Dimitrov et al., 2015; S&P, 2009), post-FC initial loan spreads are expected to be lower for loans with a rating trigger. In addition, committing to a rating trigger when CRA monitoring is strong sends a positive signal to lenders about the borrower's type, which is likely to earn the borrower lower spreads on their loans.

Results from empirical tests, however, paint a somewhat different picture. Specifically, loan spreads are higher in the post-FC period for all types of loans, including loans with a rating trigger. This result is not driven by the different borrower composition in the post-FC period, and could be because banks simply did not have the capacity to absorb the substantially higher cost of regulatory compliance in a period of low interest rates (GCFP, 2017; McKinsey & Co., 2018). Inconsistent with the predictions, the increase in loan spreads was even higher for loans with a rating trigger than that for other loans. Subsample analyses provide a further nuance in this relationship. Results suggest that firms with a high concentration of public debt in their capital structure are rewarded with lower interest rates when they choose ratings over other performance metrics in PP provisions. Importantly, consistent with lenders responding to an increase in rating quality, the discount received by these borrowers when the contract includes a rating trigger became larger after the FC.

Since performance pricing grids specify how much the loan spread is to change following a rating movement, a change in rating informativeness may prompt lenders to

adjust the extent to which loan spreads will move when the borrower's credit rating is downgraded/upgraded. If lenders perceive ratings to be of higher quality, pricing grids will likely reflect this by specifying a bigger change in loan spreads when the borrower's rating is downgraded or upgraded. This is an arguably cleaner test for examining the consequences of a change in rating quality than the tests discussed earlier, as it helps to avoid the confounding effects of the reputational damage to ratings. Consistent with the earlier evidence, results indicate that a change in credit ratings has greater consequences for borrowers in the post-FC period than in the pre-FC period. Specifically, a one-notch decrease (increase) in a borrower's credit rating leads to, on average, a 15 basis point increase (12 basis point decrease) in loan spreads in the pre-FC period, but to a 22 basis point increase (20 basis point decrease) in the post-FC period.

This chapter makes several contributions. First, it contributes to the credit rating literature by examining an important channel through which tighter rating standards affect rated firms, namely, debt contracting. It expands our understanding of how rating usages changed after the FC by showing that despite the potential reputational costs, lenders continued using rating triggers when the benefits from the improvement in rating quality were likely to be high. It also provides evidence on how increased rating quality affects not only initial loan spreads but also future loan spreads through its impact on the structure of pricing grids. To the best of my knowledge, this is the first study to explore the structure of performance pricing grids in detail and provide evidence on how lenders incorporate a change in information quality into pricing grids.

In a related study that examines the impact of rating quality on bond pricing, Badoer et al. (2019) find that bond investors raise yields when the borrower's issuer-paid rating is higher than its investor-paid rating. Unlike Badoer et al. (2019), this chapter focuses on

the use of rating triggers in private debt contracts and the pricing of loans with such provisions. In doing so, it contributes to performance pricing literature. Moreover, the setting examined in this chapter provides lenders with additional incentives that affect the impact of rating quality on debt contracting. Taken together, results from this chapter also corroborate the CRAs' claims and the findings of prior studies that regulatory scrutiny and public pressure in the wake of the FC has led to better rating quality.

The rest of the chapter is organized as follows. Section 3.2 provides a review of the PP literature. Section 3.3 develops predictions. Section 3.4 discusses sample selection and descriptive statistics. Section 3.5 discusses results from univariate tests. Section 3.6 discusses results from multivariate tests. Section 3.7 concludes.

3.2 Prior research on performance-sensitive debt

Prior studies examining performance-sensitive debt contracts have mainly focused on accounting-based PP provisions or PP provisions in general. Of the loan contracts (provided to corporates) that include such provisions, around 31% rely on credit ratings and 63% on account ratios. The major benefit of using PP provisions is that they shift a significant part of credit risk to the borrower by reducing the incentives for borrowers with improving credit quality to refinance and allowing lenders to extract higher interest from borrowers with deteriorating credit quality (Dichev, Beatty, & Weber, 2002). Prior research finds that renegotiation is delayed when a debt contract includes a PP provision (Roberts, 2015). Consistent with this result, the use of these provisions is also positively associated with expected renegotiation costs and negatively associated with renegotiation intensity (Ferracuti & Morris, 2017; Nikolaev, 2018; Saavedra, 2017).

The main analytical studies examining the use of PP provisions in debt contracts are Bhanot and Mello (2006) and Manso, Strulovici, and Tchistyi (2010). Bhanot and Mello (2006) model the change in shareholder behavior when the debt contract includes a rating trigger. Their model predicts that shareholders of a firm with low-to-medium risk and with operating flexibility avoid high-risk strategies to decrease the probability of reaching the trigger. This strategy is value-enhancing for both the debtholders and the shareholders. Manso et al. (2010) examine why firms agree to performance-sensitive debt in the first place. The main prediction of their model is that although the existence of performance-sensitive debt leads to earlier default and lower equity value compared to fixed-rate debt, it can be used as an inexpensive screening device by lenders. Therefore, firms can signal their type by committing to performance-sensitive debt. This result is consistent with those documented by Demiroglu and James (2010), who find that choosing tighter covenants conveys information about the positive future changes in covenant variables, investment and financial policies, and the outcome of covenant violations.

Asquith et al. (2005) provide the first large-sample empirical examination of the use of PP provisions in debt contracts. Results from their study indicate loan contracts are more likely to have an interest-decreasing PP provision when the borrower's probability of prepayment is high and when it is difficult for the lender to determine the borrower's risk level (i.e., high adverse selection).[19] Lenders are more likely to include interest-increasing PP provisions when there is a greater probability that the debt will be downgraded. In these cases, the borrower receives a lower initial interest rate on the loan

[19] In an interest-increasing pricing grid, the contract determines an initial interest rate and specifies how much the interest rate will increase if the borrower's financial ratios or credit rating deteriorate. The opposite is true for interest-decreasing pricing grids: the contract specifies an initial interest rate and allows for automatic downward adjustments to the interest rate as a certain ratio or the credit rating improves.

to compensate for higher potential future costs. Contracts with a higher probability of moral hazard are also more likely to include an interest-increasing PP provision.

Beatty and Weber (2003) examine whether debt contract provisions affect the borrower's accounting choices. They find that an income-increasing accounting change is more likely to occur if the firm's debt contracts allow the changes to affect contract calculations. Notably, this increase is observed only in firms whose contracts have PP provisions and dividend restrictions. Tchistyi, Yermack, and Yun (2011) investigate the factors associated with CEOs' preferences regarding performance-sensitive debt. Results suggest managers choose steeper pricing grids when their compensation is more sensitive to stock volatility but flatter pricing grids when their compensation is more sensitive to stock price changes. Fang, Li, Xin, and Zhang (2016) find that financial statement comparability is associated with a higher likelihood of including PP provisions in loan contracts.

The studies that are closest in spirit to this chapter are Ball, Bushman, and Vasvari (2008) and Costello and Wittenberg-Moerman (2011). Ball et al. (2008) examine whether the debt-contracting value of accounting information, defined as the ability of accounting information to capture credit quality deterioration, affects the structure of loan syndicates and debt contracts. The main argument proposed in the study is that higher debt contracting value of accounting information leads to lower information asymmetry between the lead arranger and other syndicate participants and more informative financial ratios. Consistent with this argument, they find that lenders are more likely to rely on accounting ratios rather than credit ratings in PP provisions as the debt-contracting value of accounting information increases. Costello and Wittenberg-Moerman (2011) provide evidence suggesting lenders reduce reliance on accounting-based PP provisions (and

financial covenants in general) and increase reliance on rating triggers when the borrower reports a material internal control weakness.[20] What differentiates this chapter from the two studies is that the setting examined in this chapter is likely to provide lenders and borrowers with incentives that may distort the relationship between information quality and its use in debt contracts. In addition, unlike the abovementioned studies, this chapter explores the impact of a change in rating quality on loan spreads, and in doing so, provides a detailed examination of the structure of pricing grids.

3.3 Predictions

3.3.1 Rating quality and the use of rating triggers

The main predictions of this chapter are predicated on the idea that a change in rating quality after the FC is likely to be reflected in how various contract terms changed from the pre-FC to the post-FC period. In a scenario where ratings are more informative but more costly to use in contracts, lenders would have to trade off the reputational costs of relying on ratings with the benefits from increased rating informativeness when deciding on whether to include a rating trigger in a loan contract. As a result, lenders might have retained or increased their use of rating triggers when the increase in rating informativeness was high, and reduced it in other cases. This argument is based on the prior literature's finding that the likelihood of a signal being included in a debt covenant or PP provision increases in its informativeness (Ball et al., 2008; Costello & Wittenberg-Moerman, 2011; Demerjian, 2017). Consequently, if tighter rating standards after the FC led to higher rating quality, I expect the effect documented in deHaan (2017) to be either

[20] Consistent with these findings, Chan, Chen, and Chen (2013) document an increase in lenders' use of accounting-based PP provisions when the firm adopts clawback provisions authorizing the board to recover compensation paid to executives when the company restates its financial reports.

muted or reversed in loans provided to firms that experienced a greater increase in CRA scrutiny in the post-FC period. On the contrary, if the changes in rating standards made ratings less informative (as per Dimitrov et al. (2015)), I expect the decrease in the use of rating triggers to be even stronger in loans provided to such firms.

I also examine whether lenders' reputational concerns after the FC were in fact the main driver of the decline in the use of rating triggers. To better understand the reputational costs of relying on ratings for lenders, it is important to recognize that the whole financial system went through structural changes in the post-FC period. Specifically, banks themselves came under heavy regulatory scrutiny in the wake of the FC due to their excessive risk-taking (The Financial Crisis Inquiry Commission, 2011). Much of Dodd-Frank and ensuing regulatory reforms were aimed at ensuring that banks take adequate steps to better manage their risk-taking behavior and improve their financial cushion. In the meantime, investor sentiment towards banks had been falling sharply and banks' profitability was expected to decline due to tighter regulations (Committee on the Global Financial System, 2018). It is estimated that the restrictions imposed by sweeping regulatory reforms following the FC tied up nearly 40 billion US dollars to this end, which, in turn, had a significant negative impact on the profitability of financial institutions (Clozel & Ackerman, 2019). At a time when banks were facing these challenges, lawmakers were concurrently pushing for reduced reliance on credit ratings in federal regulations, and investors had become more cautious regarding the extent to which they use ratings in their investment decisions (CFA Institute, 2014).

Not all banks were subjected to the same degree of regulatory pressure and public criticisms, however. For example, capital adequacy requirements brought about by new regulations were higher for systemically important financial institutions, also known as

"too-big-to-fail" banks (see Walter (2019) for more details). Dodd-Frank also gave the Federal Reserve new powers to regulate these institutions and took steps to gradually eliminate the government bailout of systemically important banks upon default.[21] Despite not being subjected to similar regulatory changes as commercial banks, investment banks were heavily criticized for their role in providing CRAs with incentives to inflate ratings (Story, 2010). In its report, The Financial Crisis Inquiry Commission even accused investment banks of "[paying] handsome fees to the rating agencies to obtain the desired ratings." Severe public and regulatory pressure eventually resulted in Morgan Stanley and Goldman Sachs giving up their investment bank status and subjecting themselves to tighter regulations as commercial banks (Kollewe & Teather, 2008). Therefore, if lenders' reputational concerns were indeed the main driver of the decrease in the use of rating triggers, I expect this decrease either to be driven by or to be more likely in loans originated by systemically important institutions and/or investment banks.

3.3.2 Rating quality and loan spreads

A change in rating quality may affect loan spreads in two ways. First, it may affect the initial interest charged on loans with a rating trigger. Referring back to our earlier discussion, Asquith et al. (2005) find that loan contracts are more likely to include interest-increasing PP when downgrades are more likely, and that loans with interest-increasing PP receive lower initial interest rates due to the higher potential future costs for the borrower. As discussed in Chapter 2, ratings are lower, and downgrades are more likely after the FC due to reduced rating inflation (deHaan, 2017; Dimitrov et al., 2015). Consequently, after the FC, lenders may have rewarded borrowers with lower initial

[21] In fact, some systemically important financial institutions were downgraded after the crisis due to lower probability of government bailouts that resulted from these regulatory reforms. For an example, see Moody's rating action on Bank of America in September 2011 (Moody's Investors Service, 2011).

interest rates when the debt contract included a rating trigger because tying the loan spread to a credit rating increases the expected cost of borrowing in an environment of more likely downgrades. Moreover, akin to the signaling hypothesis of Manso et al. (2010), committing to a rating trigger when CRA monitoring is stronger may send a positive signal to the lenders about the borrower's type, which, in turn, is likely to earn them a lower spread.

Second, a change in rating quality may affect the extent to which the loan spread moves when the borrower's rating is downgraded or upgraded as specified in the pricing grid. If lenders perceive ratings to be of higher quality, pricing grids will likely reflect this by specifying a bigger change in loan spreads in response to rating movements. The reasoning behind this prediction is that higher quality information will move loan spreads to a greater extent. Alternatively, if a loan contract's inclusion of a rating trigger after the FC is positively associated with the extent to which the quality of the borrower's credit rating has improved since the pre-FC period (as discussed in subsection 3.3.1), the average rating quality for the sample of borrowers with a rating trigger would be higher in the post-FC period than in the pre-FC period.[22] In this scenario too, rating movements would have a greater impact on loan spreads after the FC. A decrease in rating quality would have the opposite effect. Comparing how rating movements affect loan spreads in the post-FC period with that in the pre-FC period can thus provide us with additional evidence regarding the direction of the change in rating quality.

[22] The difference between the two scenarios is that the first scenario is likely to (but not necessarily) arise if the sample of borrowers with a rating trigger are essentially similar between the two periods, whereas the second scenario is built on the premise that a change in rating quality is likely to lead to a change in the sample of borrowers with a rating trigger.

3.4 Sample and descriptive statistics

3.4.1 Sample selection and variable definitions

I start with all loans syndicated in the US for which sufficient data are available to calculate the independent variables from 2005 to 2012. Loans provided to banks, diversified financials, and insurance companies are excluded from the main sample. Following prior studies, from the loans that include a PP provision, only those that rely on credit ratings or accounting information are retained in the sample to facilitate a direct comparison between the two types of loans.[23] Loan data is obtained from Thomson Reuters's Dealscan database. Dealscan reports data on loan deals – also called loan packages – where each loan package comprises loan facilities (i.e., individual loans). The vast majority of loan packages have a maximum of three loan facilities, with half of the loan packages having only one facility. Data on firm characteristics are obtained from Compustat.[24] S&P's issuer ratings are obtained from Capital IQ, and Moody's issuer ratings (if necessary) are hand-collected. All tests are performed on facility-level data.

The main empirical strategy employed in this chapter is to examine the changes in the use of rating triggers, the pricing of loans with rating triggers, and the structure of performance pricing grids from the pre-FC to the post-FC period. The financial crisis period (*FC*) is defined as the period spanning the years 2008 and 2009. A loan is considered to be issued in the FC period if the loan start date from Dealscan is between January 2008 to December 2009. The pre-crisis (*PreFC*) and the post-crisis (*PostFC*) periods cover the three years before and after the *FC* period, respectively. I isolate 2008 and 2009 from the rest of the sample because they were marked by high uncertainty due

[23] Since the vast majority of loans with PP provisions rely on either of these two types of information, the effect of this filtering on sample size is minimal. Including them in tests does not affect inferences.
[24] I use Chava and Roberts (2008) linking table to match Compustat with Dealscan.

to frequent changes to rating methodologies (especially those related to issuer ratings and bond ratings) and expectations about the new regulations. The ending month of the FC period is chosen to reflect the fact that although Dodd-Frank was signed into law in 2010, the initial version of the bill passed the House of Representatives in December 2009.

All firm characteristics are measured in the fiscal year prior to the loan origination. The definitions of all variables used in univariate and multivariate tests are also provided in Appendix A or Appendix I. *FIRMSIZE* is the natural log of the borrower's annual sales. *LEV* is calculated as the sum of short-term and long-term debt divided by the book value of assets. *ROA* is calculated as net income divided by total assets. *WCAP* is calculated as current assets minus current liabilities, divided by total assets. *RATING* is the borrower's issuer rating and is included to control for borrowers' credit quality. I use S&P's issuer ratings and augment it with Moody's ratings if the borrower is not rated by S&P. *RATING* takes the value of 22 for the highest rating (S&P's rating of AAA or Moody's rating of Aaa) and 1 for the lowest rating (S&P's rating of D or Moody's rating of C).[25]

With respect to loan characteristics, *MATURITY* is the natural log of loan maturity in months. *LOANSIZE* is the natural log of the loan amount in millions. *NUMOFCOV* and *NUMOFSWEEPS* are the number of financial covenants and sweeps included in the debt contract, respectively.[26] *NUMOFAR* is the number of lead arrangers, whereas *NUMOFLEN* is the total number of lenders participating in the loan syndicate. *SPREAD* is defined as the loan spread over LIBOR. *REVOLVER* equals one if the loan is a revolving credit line, and zero otherwise. *SECURED* equals one if the loan is secured,

[25] Since both the CC and C ratings from S&P roughly correspond to Moody's Ca rating, I set both to 2 to make the number of rating categories from S&P and Moody's equal. Appendix B provides a table specifying the numbers corresponding to each issuer rating from S&P and Moody's.

[26] A sweep is an agreement between the borrower and lenders regarding what percentage of the proceeds from pre-specified transactions should be used toward repayment. The commonly used sweeps are excess cash flow sweep, asset sale sweep, debt issuance sweep, equity issuance sweep, and insurance proceeds sweep.

and zero otherwise. Finally, *INTDEC* (*INTINC*) equals one if the loan contract includes an interest-decreasing (interest-increasing) pricing grid, and zero otherwise.

3.4.2 Descriptive statistics

Table 1 reports descriptive statistics on firm and loan characteristics for the three periods and the three subsamples of loans separately. Descriptive statistics suggest that loans with a rating trigger have significantly different characteristics than loans with accounting-based PP provisions in both the pre-FC and the post-FC periods. Specifically, loans with a rating trigger are bigger; have shorter maturity; have more arrangers and participants; are less likely to be secured; are more likely to be a revolving credit facility; and have fewer financial covenants and sweeps. Similarly, firms taking these loans are larger, more profitable, and more highly rated (although the difference in ROA disappears in the post-FC period). All these factors suggest that riskier loans and/or loans taken by riskier firms are more likely to include accounting-based PP provisions than rating triggers. This is reflected in loan spreads as well, since loans with a rating trigger have significantly lower spread than those with accounting-based PP provisions.

[INSERT TABLE 1]

Loans with no PP provisions are also significantly different from the other two subsamples of loans. In terms of firm size, loan size, maturity, number of arrangers, and issuer ratings, loans with no PP provisions are somewhere in between loans with accounting-based PP provisions and those with a rating trigger. They are, however, significantly more likely to be secured and likely to be provided by more leveraged and less profitable firms. Of the three subsamples of loans, they also have the highest spread in all three periods, suggesting that lenders reward borrowers with lower interest rates if

they agree to the inclusion of a PP provision. The direction of the changes in firm and loan characteristics from the pre-FC to the post-FC period are similar across the three subsamples. One notable difference is that while firms taking loans with a PP provision have significantly higher issuer ratings (about half a notch) in the post-FC period, firms taking loans with no PP provision have similar issuer ratings after the FC.

3.5 Univariate analyses

3.5.1 The use of rating triggers after the FC

Figure 1 presents the changes in the percentage of loan contracts that include rating triggers versus accounting-based PP provisions from the pre-FC period through the post-FC period. The two vertical lines indicate the end of the pre-FC and the FC periods. The downward trend in both lines suggests that there is an overall decline in the use of PP provisions after the FC. One interesting observation from the graph is that, in the wake of the financial crisis (particularly, in 2008), a sudden decline in the use of rating triggers is accompanied by a sharp increase in the use of accounting-based PP provisions. This trend is consistent with the revelations of low rating quality having reputational damage to CRAs that extended beyond asset-backed securities. Moving into 2009 and beyond, however, we observe a decrease in the use of accounting-based PP provisions as well. Another interesting observation from Figure 1 is that, in 2011, there was a drop in the use of accounting-based PP provisions, which bounced back in 2012. This trend suggests that the results documented in deHaan (2017) regarding the recovery of rating usage (albeit

insignificant) in later years may have at least partially been driven by the decrease in accounting-based PP provisions, not by the increase in the use of rating triggers.[27]

[INSERT FIGURE 1]

3.5.2 The structure of performance pricing grids

Table 2 provides the descriptive statistics related to important dimensions of pricing grids (see appendix C for an example of how the variables in this table are calculated). Consistent with the argument that ratings are of higher quality after the FC, the change in loan spreads should the borrower's rating be downgraded/upgraded is about 7.5-8 basis points higher in the post-FC period than in the pre-FC period (column 3, rows 3 and 4).[28] Controlling for issuer rating does not affect inferences. Results from additional tests (untabulated) also indicate this increase is stronger (significant at 5%) when the sample is restricted to firms that took out a loan with a rating trigger in both the pre-FC and the post-FC periods. The result that the effect documented in initial tests is stronger in the restricted sample has two implications. First, it suggests the sample of borrowers whose loan contracts included a rating trigger changed from the pre-FC to the post-FC period, providing initial evidence in support of the argument that the change in rating quality after the FC had an impact on whether a loan contract would include a rating trigger. Second, it suggests that the inferences from initial tests are robust to a potential sample selection bias.

[INSERT TABLE 2]

[27] When the analysis is restricted to the sample of loans with PP provisions, a decrease in the proportion of loans with accounting-based PP provisions will automatically increase the proportion of loans with a rating trigger within the PP sample even when there is no change in the use of rating triggers.
[28] As a comparison, this increase is significantly smaller and more asymmetric for accounting-based pricing grids (column 6, rows 3 and 4).

Several other observations from Table 2 are noteworthy. First, rating-based pricing grids are more detailed than accounting-based pricing grids in both the pre-FC and post-FC periods (row 1). For both subsamples of loans, the initial interest rate is usually set in the middle of the pricing grid, suggesting that the majority of pricing grids allow for both an increase and a decrease in initial interest rates when the borrower's financial performance improves/deteriorates (row 2). Second, the increase (decrease) in loan spread should a borrower's performance deteriorate (improve) is lower for loans with a rating trigger than those with accounting-based PP provisions (rows 3 and 4). This result could partially be driven by the difference in credit quality between firms with rating triggers and those with accounting-based PP provisions (i.e., different mean issuer ratings, as shown in row 10).[29] Third, in both periods, the increase in loan spread should a borrower's rating be downgraded is higher than the decrease in loan spread should a borrower's rating be upgraded (comparison of rows 3 and 4). Hence, borrowers are penalized to a greater extent for a rating downgrade than they are rewarded for a rating upgrade. The opposite is true for accounting-based pricing grids. This result is unlikely to be driven by the better credit quality of borrowers with rating triggers as controlling for issuer rating only increases this difference.

Finally, the change in loan spreads as the borrower's performance changes (i.e., across different levels of a pricing grid) is asymmetric with respect to both the direction of the change and the type of the provision. A comparison of row 3 with row 5 reveals that in rating-based pricing grids, the increase in the loan spread gets even bigger as the borrower's credit rating falls (see appendix C for a relevant example). On the contrary, the subsequent decrease in the loan spread when the borrower's credit rating further

[29] Controlling for issuer rating partially eliminates this difference. However, it should be noted that this test may be biased as not all firms that take loans with accounting-based PP provisions have issuer ratings.

improves is generally lower than the previous decrease in the loan spread. These findings suggest that the marginal benefit of a rating upgrade decreases for changes up the rating scale, while the marginal cost of a rating downgrade increases for changes down the rating scale. This pricing grid structure is unique to rating-based grids and is not evident in accounting-based pricing grids.

3.5.3 Pricing of loans with a rating trigger after the FC

Figure 2 presents the change in loan spreads from the pre-FC period through the post-FC period. Several observations from this figure are noteworthy. First, loan spreads are higher in the post-FC period than in the pre-FC period for all three subsamples of loans. This increase is unlikely to be driven by the change in the composition of borrowers as surveys of banking practices suggest that banks became more selective of firms they lend to after the crisis (GCFP, 2017; McKinsey & Co., 2018). These survey results are also consistent with the overall direction of the changes in loan and firm characteristics as documented in subsection 3.4.2. Controlling for various factors and/or limiting the sample to firms that borrowed in both periods provide similar inferences (untabulated). One likely explanation for the increase in loan spreads after the FC is that banks simply didn't have the capacity (or willingness) to absorb the substantially higher cost of regulatory compliance in an era of ultra-low interest rates and reduced exposure to higher risk investments (e.g. GCFP, 2017; McKinsey & Co., 2018).

[INSERT FIGURE 2]

Second, the increase in loan spreads in the post-FC period is significantly *higher* for loans with a rating trigger than that for other loans. The increase in loan spreads is, on average, 70 basis points for loans with accounting-based PP provisions and no PP

provisions, and 93 basis points for loans with a rating trigger. As a result of this differential increase, the 97-basis points difference in loan spreads that existed in the pre-FC period between loans with a rating trigger and loans with accounting-based PP provisions fell to 73 basis points in the post-FC period. This is even though firms with loans that include a rating trigger are bigger and have higher issuer ratings in the post-FC period. Similarly, the average increase in the issuer ratings of firms with rating triggers is not statistically different from those with accounting-based PP provisions.

3.6 Multivariate analyses

3.6.1 Decline in the use of rating triggers – robustness tests

Before testing the study's predictions, I first replicate the finding that the use of rating triggers decreased after the crisis and test if this finding is robust to selection bias, because the sample of debt contracts that include a PP provision is unlikely to be random. The base model is defined as:

$$BINRATTR = \alpha_0 + \alpha_1 FC + \alpha_2 PostFC + \alpha_3 MATURITY + \alpha_4 SECURED + \alpha_5 LOANSIZE + \alpha_6 REVOLVER + \alpha_7 FIRMSIZE + \alpha_8 LEV + \alpha_9 ROA + \alpha_{10} RATING + Industry\ fixed\ effects \quad (1)$$

where the equation is estimated using probit. The dependent variable, *BINRATTR*, equals one if the debt contract includes a rating trigger and zero if it includes an accounting-based PP provision. The rest of the variables are as defined in subsection 3.4.1 (also provided in Appendix A and Appendix I). Unlike deHaan (2017), I include the FC period in my analysis. In another departure from deHaan (2017), and following Costello and Wittenberg-Moerman (2011), I do not drop the firms without a credit rating and instead assign the value of zero to *RATING* if the borrower does not have an issuer rating.

Restricting the sample to borrowers with an issuer rating biases the sample toward the loans with a rating trigger as firms with rating triggers, unlike those with accounting-based PP provisions, almost always have an issuer rating.[30]

To incorporate the information provided by loans with no PP provisions into the analysis, I employ Heckman (1976) correction using full information maximum likelihood (where the loans with no PP provisions are censored) and multinomial logit models.[31] The use of the latter is made possible due to a unique feature of the data, that a loan contract including a rating trigger rarely includes an accounting-based PP provision (less than 1% of loan contracts). I drop these observations from the sample to use multinomial logit as this model assumes only one alternative is chosen from among the alternatives at any given time.[32] I use two different models to correct for the selection bias because each has its drawbacks and advantages. The Heckman correction model allows for a more straightforward interpretation of the results but requires the use of instruments for identification purposes. The advantage of the multinomial logit model is that it allows the use of full loan sample without the need for an instrument, but comes at a cost of an additional assumption, which is the independence of irrelevant alternatives. This assumption requires that a borrower not choosing one alternative is equally likely to choose the second alternative over the third.

The selection model for Heckman correction is:

$$PP = \partial_0 + \partial_1 FC + \partial_2 PostFC + \partial_3 MATURITY + \partial_4 SECURED + \partial_5 LOANSIZE + \partial_6 REVOLVER + \partial_7 FIRMSIZE + \partial_8 LEV + \partial_9 ROA +$$

[30] In rare cases, a borrower will have a senior debt rating but not an issuer rating. Since rating triggers predominantly use senior debt ratings, some borrowers have a loan that includes a rating trigger but does not have an issuer rating.

[31] Unfortunately, the nature of the data does not allow the use of nested logit because the alternatives are not observable. E.g., I do not observe the characteristics of alternative loan packages that were available to, but were not accepted by, the firm when the outcome is a loan contract that includes a PP provision.

[32] For consistency, I drop these loan contracts from the sample when using Heckman selection as well.

$$\partial_{10}RATING + \partial_{11}NUMOFLEN + \partial_{12}NUMOFAR + \partial_{13}REFIN + \partial_{14}REL + Industry\ fixed\ effects \quad (2)$$

where *PP* equals one if the loan contract includes a performance pricing provision, and zero otherwise. The equation includes four variables that are not present in equation (1) for identification purposes. To the best of my knowledge, this is the first study to use Heckman correction in the context of PP provisions, so I refer to findings from prior literature in identifying factors that are likely to affect the decision of including a PP provision in a debt contract without affecting the decision of choosing one type of PP provision over the other. From the instruments, *NUMOFLEN* and *NUMOFAR* are as defined in subsection 3.4.1. *REL* equals one if the lead arranger of the loan has been a lead arranger for any of the loans taken by the same company within the last five years (i.e., if the lead arranger is a relationship bank), and zero otherwise. *REFIN* equals one if the loan refinances a prior deal, and zero otherwise.

The choice of the instruments is mainly motivated by the findings from Asquith et al. (2005). First, the likelihood that a debt contract includes a PP provision is associated with the moral hazard and information asymmetry between the borrower and its lenders (Asquith et al., 2005). In light of prior literature's finding that lead arrangers form a more concentrated syndicate when there is high moral hazard (Sufi, 2007), I expect syndicate size (i.e., the number of arrangers and participants) to be associated with the use of PP. Moreover, the role of PP as an inexpensive screening device may become more valuable as syndicate size increases (Manso et al., 2010). Second, since a previous lending relationship is likely to reduce the information asymmetry between the borrower and its lenders, PP is less likely to be used in loans provided by relationship banks. Finally, refinancing deals are more likely to include a PP provision since refinancing is costly for

both parties, and the use of PP provisions can lower the likelihood of future refinancing (Asquith et al., 2005).[33]

The first column of Table 3 Panel A presents results for the base model. Standard errors are obtained using the bootstrapping method. All continuous independent variables are winsorized at 1% percent extremes. Results from column 1 suggest that the decrease in the use of rating triggers started in the FC period and strengthened in the post-FC period. The latter result confirms the findings from deHaan (2017). In terms of independent variables, smaller loans, secured loans, and loans with higher maturity are less likely to include a rating trigger. While larger firms and firms with high ratings are more likely to opt-in for a rating trigger than for an accounting-based PP provision, firms with higher ROA are less likely to do so. This is intuitive, as firms with higher cash flows (firms with higher ratings) would be more likely to opt-in for a cash flow-based ratio (credit rating) in their debt contracts.

The second column of Table 3 Panel A presents results from the maximum likelihood probit model with sample selection, where the selection model is provided in column 3. The dependent variable in the second column, *RATTR,* equals one if the loan contract includes a rating trigger, and zero otherwise (when censored at *PP*, it becomes identical to *BINRATTR)*. Results from the selection model suggest that there has been a decline in the use of PP provisions from the pre-FC to the post-FC period (but not in the FC period), confirming the trend documented in Figure 1. In terms of instruments, the use of PP provisions is more likely in larger syndicates and refinancing deals, and less likely when the lead arranger is a relationship bank. The number of lead arrangers is not

[33] While there are reasons to believe that these four variables are likely to be associated with the use of PP provisions in general, it is not clear why they would be more likely to be associated with one type of provision than the other. In fact, these variables are not significant when added to the second stage regression (instead of being used as instruments). When the instruments are added to the first stage equation, pseudo-R^2 improves from 18.8% to 25.3%, suggesting that, jointly, the instruments are reasonably strong.

significantly associated with the use of PP provisions. Rho is significantly positive at 5%, suggesting that failure to correct for the selection bias may lead to biased coefficients. Importantly, however, correcting for this bias makes the coefficient on *PostFC* even larger in absolute value (the difference is significant at 5%).

[INSERT TABLE 3]

Table 3 Panel B presents results from the multinomial logit model where the right-hand side variables are the same as in equation (1) and the dependent variable is *PPCOV*. *PPCOV* equals zero if the debt contract does not include a PP provision, one if the contract includes an accounting-based PP provision, and two if the contract includes a rating trigger. For interpretation purposes, multinomial logit models set the coefficients on independent variables for one of the outcomes (called the base outcome) to one, and present the coefficients for other outcomes relative to coefficients for the base outcome. To enable a direct comparison among all three choices, however, I also add a third column where the base outcome is one of the alternative outcomes in the first two columns. Since all three columns are an output of a single regression, the sum of the coefficients from columns one and three equals the coefficients from column 2.

The coefficients presented are the logarithm of relative-risk ratios. In the first two columns of Panel B, *PPCOV* value of zero (no PP provision) is set to be the base outcome. Confirming the results from the selection model in Panel A, results from columns 1 and 2 suggest that the odds of a loan contract including an accounting-based PP provision or a rating trigger decreased from the pre-FC period to the post-FC period. However, this decrease was stronger for rating triggers than for accounting-based PP provisions as seen in column three (*FC* and *PostFC* significantly negative at 1%).

Next, I test if the documented results are simply driven by the change in the composition of borrowers from the pre-FC to the post-FC period, and use maximum likelihood probit with sample selection for this test. The dependent variable in the selection model, *STAYIN*, equals one if a firm borrowed in both the pre-FC and the post-FC periods, and zero otherwise. Hence, loans taken by firms that appear in the pre-FC sample but not in the post-FC sample (or vice versa) are censored in the main regression.

The independent variables in the selection model include firm characteristics from equation (1) plus five instruments. These additional variables are intended to capture borrowers' credit quality and alternative sources of borrowing since they are likely to be the most salient reasons for firms' exiting or entering the sample. *CFTLIAB* and *CFTCURLIAB* are calculated as operating income before depreciation and amortization divided by total liabilities and current liabilities, respectively. *CFTCAPEX* is calculated as operating income before depreciation and amortization divided by capital expenditures.[34] *CFVOL* is the standard deviation of the firm's cash flows for the last five years, where cash flows are calculated as operating income before depreciation and amortization minus taxes, divided by total assets. *PUBDEBT* equals one if the borrower issued public debt in the post-FC period, and zero otherwise. The first three variables are measured in the fiscal year prior to the loan origination.[35] Results from the selection model (column 3 of Table 4) suggest that firms with better cash flow-to-liabilities and cash flow-to-capital expenditures ratios, as well as firms with lower cash flow volatility are more likely to appear in both periods of the sample. Interestingly, firms that issued

[34] The choice of these three ratios is motivated by S&P's rating methodologies where the rating agency defines key ratios for the purposes of rating assessment (S&P, 2008b). Although this is by no means an exhaustive list of key ratios, some of the other ratios defined in rating methodologies but not calculated here (such as leverage ratio) are captured by the control variables defined earlier.

[35] Together, these five variables increase the pseudo-R^2 of the selection model from 12% to 17.5% and are generally insignificant when directly added to equation (1).

public debt in the post-FC period were also more likely to borrow from banks in both periods.

[INSERT TABLE 4]

The first and second columns of Table 4 present results from regressions that estimate equation (1) only for firms that appear in both periods of the sample, which leads to the censoring of about one-third of the original sample. The difference between the first and the second column is that column 2 regression also includes a correction for the sample selection bias. However, rho is not significantly different from zero, suggesting that not correcting for the selection bias does not bias the coefficient estimates (provided that the selection model uses reasonably strong instruments). Comparing either of these models with the first column of Table 3 Panel A reveals that restricting the sample in this way makes the coefficient on *FC* larger (in absolute value) than the coefficient on *PostFC*. Interestingly, the coefficient on *PostFC* in Table 4 is statistically similar to the coefficient on *PostFC* when we do not restrict the sample to *STAYIN* firms but correct for the selection bias as in Table 3 Panel A. Other interesting observations are that, once the sample is restricted, *ROA* loses its significance, while leverage gains significance. In untabulated tests, I also estimate a multinomial probit model with sample selection, which yields similar results. Taken together, a battery of multivariate tests expands on the univariate analyses, and unambiguously suggests that the use of rating triggers relative to accounting-based PP provisions has decreased after the crisis.

3.6.2 The use of rating triggers after the FC – regulatory scrutiny vs rating quality

Having confirmed that the decrease in the use of rating triggers from the pre-FC to the post-FC period is robust to different model specifications, I proceed with testing the

study's main predictions. First, I examine whether the decrease in the use of rating triggers was stronger in or driven by the loans originated by systemically important financial institutions or investment banks. *INVBANK* equals one if at least one of the lead arrangers of the syndicate is identified as an investment bank, finance company, mutual fund or pension fund in Dealscan, and zero otherwise. *SIFI* equals one if at least one of the arrangers of the syndicate was defined as a systemically important financial institution during or immediately after the financial crisis, and zero otherwise (Financial Stability Board, 2011).

The empirical strategy for testing this prediction is to interact *INVBANK* or *SIFI* with *FC* and *PostFC* in a probit model with sample selection (as in the second column of Table 3 Panel A), and examine the marginal impact of *INVBANK* and *SIFI* on the use of rating triggers. Since the interpretation of coefficients on interaction terms in nonlinear models is different from that in linear models, the coefficients from these regressions are not presented. Instead, the probabilities that a given loan contract includes a rating trigger – calculated from the output of these regressions – are presented separately for loans originated by *SIFI* (*INVBANK*) and non-*SIFI* (non-*INVBANK*) lenders. Below that output, the changes in those probabilities from the pre-FC to the FC and post-FC periods are presented. Comparing the changes from the pre-FC to the post-FC period between *SIFI* (*INVBANK*) and non-*SIFI* (non-*INVBANK*) subsamples is akin to interpreting a coefficient on an interaction term in linear models.

Results from *INVBANK* tests (Table 5 Panel A) suggest that, controlling for firm and loan characteristics, investment banks were more likely to use rating triggers in the pre-FC period. The probability of using a rating trigger fell significantly from the pre-FC to the post-FC period for both the investment banks (from 0.336 to 0.220) and the commercial banks (from 0.259 to 0.218), but the decrease was stronger for investment

banks. As a result of this change, the difference that existed between *INVBANK* and non-*INVBANK* subsamples in the pre-FC period disappeared in the FC and post-FC periods, falling from 0.077 to 0.002. The decrease in the use of rating triggers for the *SIFI* subsample, however, was not significantly different from that for the non-*SIFI* subsample (Panel B).[36] Taken together, these findings provide some support for the argument that lenders facing greater regulatory criticisms and investor pressure after the FC reduced the use of rating triggers to a greater extent.

[INSERT TABLE 5]

Next, I perform two tests to investigate whether the decrease in the use of rating triggers was muted or reversed for the subsample of borrowers for whom CRA monitoring tightened to a greater extent in the post-FC period, assuming that tightening the CRAs' monitoring of firms increases the informativeness and reliability of ratings assigned to those firms. First, I partition the sample into two based on the Z-score of borrowers with the same issuer rating and examine the change in the use of rating triggers for each subsample (this partitioning is repeated every year) (Altman, 2000).[37] Within each rating notch, CRAs' scrutiny of borrowers with worse fundamentals (*HIZSCORE* value of zero) is likely to be tightened to a greater extent in the post-FC period than that of borrowers with better fundamentals (*HIZSCORE* value of one), because lack of timeliness was one of the most criticized aspects of ratings in the wake of the FC. Second, I partition the sample into two based on whether the firm predominantly issues public debt. *HIPUBD* takes the value of one if 80% or more of the firm's debt consists of bonds and notes (about 25% of the sample). The rationale behind this partitioning is that ratings are arguably

[36] Inferences remain unchanged if I restrict the analysis to only the sample of commercial banks, where *SIFI* is also redefined to include only commercial banks.
[37] Altman's (2000) Z-score is calculated as 3.3 * EBIT / TA + Sales / TA + 1.4 * Retained Earnings / TA + 1.2 * WCAP / TA + 0.6 * Market value of equity / Total Liabilities, where TA is total assets.

more important for public debt investors, and as a result, the monitoring of firms with a high concentration of public debt is likely to improve to a greater extent when the investors are less trusting (Bolton et al., 2012).[38]

Consistent with the predictions, results from the first two columns of Table 6 Panel A indicate that there was a significant decrease in the use of rating triggers for the subsample of *HIZSCORE* firms but not for the subsample of non-*HIZSCORE* firms (difference statistically significant at 5%). Also consistent with the argument that the improvement in rating quality started during the FC, there is no evidence of a significant decrease in the use of rating triggers during the FC for the subsample of non-*HIZSCORE* firms (column 1). Tests using *HIPUBD* yield similar results (columns 5 and 6 of Table 6 Panel A). Specifically, there is a significant decrease in the use of rating triggers for the subsample of non-*HIPUBD* firms but not for the subsample of *HIPUBD* firms. The difference between the subsamples in terms of the change from the pre-FC period is statistically significant at 10%. Inferences remain unchanged when I restrict the sample to firms that appear in both the pre-FC and the post-FC periods.

[INSERT TABLE 6]

In the third test, I partition the sample based on the complexity of a borrower's capital structure and examine the change in the use of rating triggers for each subsample separately. I assume that a capital structure with more types of debt is more complex, and it is harder for banks to evaluate the creditworthiness of borrowers with more complex debt structures. Therefore, increased rating quality would be more valuable for lenders in cases where the borrower has a complex debt structure, and they would be more likely to retain the use of rating triggers when the loan is provided to such a firm. I consider four

[38] Data on capital structure is obtained from Capital IQ.

types of debt for this analysis: private debt (term loans and revolving lines), public debt (bonds and notes), capital leases, and other borrowings. Consistent with the predictions, results from Table 6 Panel B suggest that the use of rating triggers decreased for the subsample of firms with simpler debt structures (one or two types of debt) but remained unchanged for the subsample of firms with more complex debt structures.

In additional tests, I redefine the FC period and repeat the analyses (untabulated). In these tests, following deHaan (2017), the FC period starts in mid-2007 and ends in mid-2009. This start date of the FC period roughly coincides with the first wave of downgrades of ratings assigned to asset-backed securities, and hence the start of criticisms directed at CRAs. Inferences from tests using the redefined FC period, as well as from tests using smaller windows for the pre-FC and the post-FC periods remain very similar to those discussed earlier. In summary, results from this section suggest that lenders retained their reliance on ratings in PP provisions in cases where rating quality likely improved to a greater extent or where increased rating informativeness was more valuable, and reduced their reliance on ratings in cases where regulatory scrutiny or reputational concerns were stronger.

3.6.3 Pricing of loans with a rating trigger after the FC

I estimate the following model using OLS to test the change in loan spreads for loans with a rating trigger:

$$SPREAD = \gamma_0 + \gamma_1 FC + \gamma_2 PostFC + \gamma_3 ACCTR + \gamma_4 RATTR + \gamma_5 ACCTR * FC + \gamma_6 RATTR * FC + \gamma_7 ACCTR * PostFC + \gamma_8 RATTR * PostFC + Control\ variables + Industry\ fixed\ effects + \epsilon \quad (3)$$

where *ACCTR* equals one if the debt contract includes an accounting-based PP provision, and zero otherwise. Other variables are as defined earlier. The main empirical approach

to testing the predictions concerning loan pricing is to compare the coefficients on *RATTR∗PostFC* to that on *ACCTR∗PostFC*. Ideally, one would use a two-stage model where the selection between PP provision versus no-PP provision or the selection between an accounting-based versus rating-based PP provision is modelled in the first stage. However, it is unclear what factors would affect these choices without affecting the loan spreads, making the identification of such an instrument very difficult. Since weak instruments may introduce additional biases in either direction, the study does not employ such a two-stage model.

The first column of Table 7 presents the model that includes all loan observations, while the second column presents the model that is restricted to the sample of firms present in both periods (*STAYIN* value of one).[39] Standard errors are obtained via bootstrapping. Results indicate that in the pre-FC period, ceteris paribus, loans with no PP provisions had the highest spread, followed by loans with rating triggers and loans with accounting-based PP provisions. As also documented in Figure 2, loan spreads for all three subsamples of loans increased from the pre-FC period to the post-FC period. The increase in loan spreads is not statistically different between the subsample of loans with accounting-based PP provisions and those with no PP provisions (*ACCTR∗PostFC* not significant). Inconsistent with the predictions, however, this increase is 13.7 and 12.5 basis points higher for loans with a rating trigger than for loans with no PP provisions and accounting-based PP provisions, respectively (both differences are statistically significant). Moreover, the additional spread increase for loans with a rating trigger fully eliminated the lower spread borrowers received when they opted in for rating triggers in the pre-FC period. Restricting the sample to *STAYIN* firms in the second column does not

[39] Since the value of rho from the maximum likelihood model with sample selection is not significant as in previous tests, I present the tests without the correction for sample selection bias. Inferences remain unaffected if I do so.

affect the inferences as the difference between the coefficients on *ACCTR* ∗ *PostFC* and *RATTR* ∗ *PostFC* remains statistically significant at 5%.

[INSERT TABLE 7]

To examine whether the change in loan spreads was different for the subsample of borrowers that experienced a greater improvement in CRA monitoring in the post-FC period, I include interaction terms between *HIPUBD* (or *HIZSCORE*) and *PostFC*. To keep the number of interactions to a minimum, I exclude the FC period and loans with no PP provisions from the analysis.[40] Results from Table 8 suggest that in both the pre-FC and the post-FC periods, non-*HIPUBD* firms received similar loan spreads when they chose either type of PP provision (*BINRATTR* statistically insignificant). *HIPUBD* firms, however, received 11 basis points lower loan spreads in the pre-FC period when the loan contract included a rating trigger rather than an accounting-based PP provision (sum of *BINRATTR* and *BINRATTR*HIPUBD* significant at 5%). Consistent with a bigger improvement in CRA monitoring of *HIPUBD* firms in the post-FC period (and hence more likely downgrades), this effect became stronger following the FC. Specifically, in the post-FC period, *HIPUBD* firms were rewarded with a 29 basis points reduction in loan spreads when the loan contract included a rating trigger rather than an accounting-based PP provision. The change from 11 to 29 basis points is statistically significant at 10%. Results are not significant when I use *HIZSCORE* instead of *HIPUBD*. Instead, firms with a lower Z-score within each rating notch receive higher loan spreads when the loan contract includes a rating trigger, suggesting confounding effects of other factors captured by *HIZSCORE* on loan spreads.

[INSERT TABLE 8]

[40] Inferences remain unchanged when I include them in the analysis.

3.7 Conclusion

This chapter seeks to understand the impact of a change in rating quality on the use of ratings in PP provisions and the pricing of loans with such provisions. Evidence suggests that lenders retained their reliance on ratings in cases where rating quality likely improved to a greater extent, and reduced their reliance on ratings in cases where regulatory pressure was stronger. Consistent with the increased rating quality after the FC affecting the terms of debt contracts, the impact of rating movements on loan spreads became stronger in the post-FC period as reflected in the structure of pricing grids. There is also evidence suggesting firms that likely experienced a bigger increase in CRA monitoring were awarded larger discounts if the loan contract relied on ratings rather than accounting numbers in PP provisions. These findings add to the existing literature by documenting how lenders incorporated the change in rating quality into different dimensions of loan contracts after the FC despite the reputational damage to ratings.

Appendix A: *Variable definitions*

Variables	Definitions
BINRATTR	Indicator that equals one if the debt contract includes a rating trigger and zero if it includes an accounting-based PP provision. No value is assigned to the variable if the debt contract does not include any PP provision.
CFTCAPEX	Ratio of operating income before depreciation and amortization to capital expenditures (measured in t-1).
CFTCURLIAB	Ratio of operating income before depreciation and amortization to total current liabilities (measured in t-1).
CFTLIAB	Ratio of operating income before depreciation and amortization to total liabilities (measured in t-1).
CFVOL	Standard deviation of the firm's cash flows for the last five years. Cash flows are calculated as operating income before depreciation and amortization minus taxes, divided by assets.
FC	Indicator for the financial crisis period (years 2008 and 2009).
FIRMSIZE	Natural log of the borrower's annual sales.
HIPUBD	Indicator if 80% or more of the firm's debt comprises bonds and notes.
HIZSCORE	Indicator if the borrower's Z-score is higher than the median Z-score of borrowers within the same rating notch in a given fiscal year. Altman's Z-score (measured at t-1) is calculated as $3.3 * \text{EBIT} / \text{TA} + \text{Sales} / \text{TA} + 1.4 * \text{Retained Earnings} / \text{TA} + 1.2 * \text{WCAP} / \text{TA} + 0.6 * \text{Market value of equity} / \text{Total Liabilities}$, where TA is total assets.
INTDEC	Indicator if the loan contract includes an interest-decreasing pricing grid.
INTINC	Indicator if the loan contract includes an interest-increasing pricing grid.
INVBANK	Indicator if at least one lead arranger is identified as an investment bank, finance company, mutual fund or pension fund in Dealscan.
LEV	Sum of short-term and long-term debt, divided by total assets (measured in t-1).
LOANSIZE	Natural log of the loan amount (in millions).
MATURITY	Natural log of loan maturity (in months).
NUMOFAR	Number of lead arrangers in a loan syndicate.

Appendix A *(continued)***:** *Variable definitions*

NUMOFCOV	Number of financial covenants in a debt contract.
NUMOFLEN	Number of total lenders in a loan syndicate.
NUMOFSWEEPS	Number of sweeps in a debt contract.
PostFC	Indicator for the post-crisis period (years 2010 through 2012).
PP	Indicator if the debt contract includes a performance pricing provision.
PUBDEBT	Indicator for borrowers that issued public debt in the post-FC period.
RATING	Issuer rating from S&P (or Moody's when the firm is not rated by S&P). In multivariate tests, the variable takes the value of zero if the firm does not have an issuer rating from either rating agency.
RATTR	Indicator if the debt contract includes a rating trigger.
REFIN	Indicator if the loan refinances a prior deal.
REL	Indicator if the lead arranger of the loan has been a lead arranger for any of the loans taken by the same company within the last five years (i.e., if the lead arranger is a relationship bank).
REVOLVER	Indicator if the loan is a revolving credit line.
ROA	Net income divided by total assets.
SECURED	Indicator if the loan is secured.
SIFI	Indicator if at least one of the lead arrangers was a systemically important financial institution during or immediately after the FC.
SPREAD	Loan spread over LIBOR.
STAYIN	Indicator for firms that took a loan in both the pre-FC and the post-FC periods.
WCAP	Working capital divided by total assets (measured in t-1).

Appendix B: *Numerical values corresponding to S&P's and Moody's ratings*

Group	Numeric value	S&P rating	Moody's rating
Investment grade	21	AAA	Aaa
	20	AA+	Aa1
	19	AA	Aa2
	18	AA-	Aa3
	17	A+	A1
	16	A	A2
	15	A-	A3
	14	BBB+	Baa1
	13	BBB	Baa2
	12	BBB-	Baa3
Speculative grade	11	BB+	Ba1
	10	BB	Ba2
	9	BB-	Ba3
	8	B+	B1
	7	B	B2
	6	B-	B3
	5	CCC+	Caa1
	4	CCC	Caa2
	3	CCC-	Caa3
	2	CC, C	Ca
In default	1	D	C
Not rated	0		

Appendix C: *Calculation of the variables in Table 2 with an example*

Below is an example of a rating-based pricing grid. This pricing grid allows for both an increase and a decrease in the initial interest rate when the firm's senior debt rating changes as specified in the contract (i.e., it is both an interest-increasing and an interest-decreasing pricing grid). For the purposes of this example, we will assume the borrower has a senior debt rating of BBB+, meaning that the initial interest rate on this loan is LIBOR plus 40 basis points. The loan spread at each level is chosen in a way that will assist in better understanding the discussion provided in subsection 3.5.2.

Level	Senior debt rating	LIBOR Plus
1	A	25
2	A-	30
3	BBB+	40
4	BBB	55
5	BBB-	75

The variables from Table 2 are defined as follows. The number of levels in this pricing grid equals 5 (equivalent of row 1 in Table 2). The initial interest rate is set at level 3 of the pricing grid (equivalent of row 2 in Table 2). The *immediate* increase in loan spread should the firm's senior debt rating be downgraded from BBB+ to BBB is 15 basis points, calculated as 55 minus 40 (row 3). The *immediate* decrease in loan spread should the firm's senior debt rating be upgraded to A- is 10 basis points, calculated as 40 minus 30 (row 4). The *average* increase in loan spread when the borrower's performance deteriorates equals 17.5 basis points, calculated as the average of the increase in loan spread from level 3 to level 4 and the increase in loan spread from level 4 to level 5 (row 5). The *average* decrease in loan spread when the borrower's performance improves is 7.5 basis points, and is calculated in a similar way (row 6). As can be seen from the pricing grid, the decrease in loan spread from level 3 to level 2 is greater than the decrease in loan

spread from level 2 to level 1, making the *immediate* decrease in loan spread in response to a rating upgrade (10 basis points) to be higher than the *average* decrease (7.5 basis points). Maximum spread reduction (increase) obtainable through the pricing grid is 15 (25) basis points (rows 7 and 8), and is calculated as the difference between the initial interest rate and the interest rate in level 1 (level 5). Finally, the difference in loan spread between the highest and the lowest level of pricing grid is 50 basis points, calculated as 75 minus 25 (row 9).

Figure 1: *Percentage of loan contracts with accounting-based versus rating-based PP provisions from 2005 through 2012*

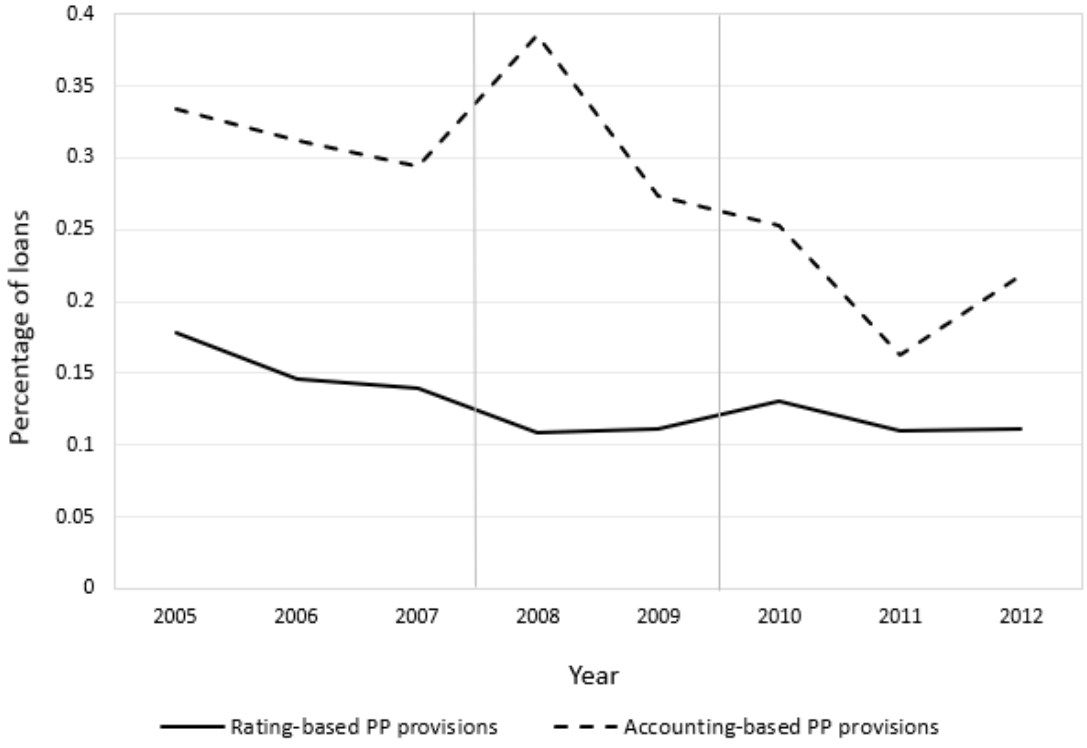

Figure 2: *Average loan spreads (in hundreds) from 2005 through 2012*

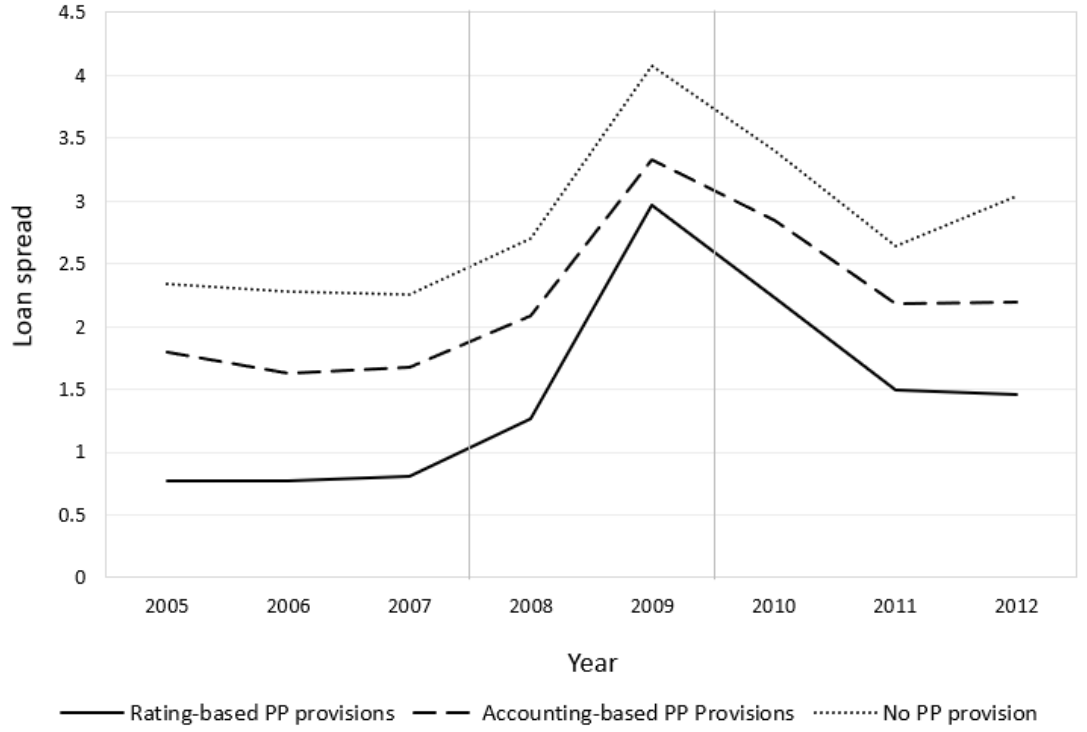

Table 1 – *Panel A*: *Descriptive statistics of loan facilities in the pre-FC period*

	Rating-based PP provision			Accounting-based PP provision			No PP provision		
Variable	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
FIRMSIZE	737	8.34	1.16	1598	6.57^{-}	1.29	1853	6.92^{-}	1.72
INTDEC	737	0.93	0.25	1598	0.82^{-}	0.38	N/A	N/A	N/A
INTINC	737	0.90	0.30	1598	0.61^{-}	0.49	N/A	N/A	N/A
LEV	737	0.29	0.17	1598	0.31	0.31	1853	0.40^{+}	0.31
LOANSIZE	737	6.33	0.95	1598	4.90^{-}	1.23	1853	4.83^{-}	1.51
MATURITY	737	3.92	0.53	1598	4.01^{+}	0.35	1853	3.98^{+}	0.58
NUMOFAR	737	1.72	0.49	1598	1.39^{-}	0.50	1853	1.43^{-}	0.52
NUMOFCOV	737	1.54	0.75	1598	2.47^{+}	0.96	1853	1.22^{-}	1.41
NUMOFLEN	737	14.66	9.01	1598	8.29^{-}	7.31	1853	5.75^{-}	7.79
NUMOFSWEEPS	737	0.58	1.30	1598	2.28^{+}	2.04	1853	1.45^{+}	1.95
RATING	626	12.71	2.43	671	8.85^{-}	1.61	1008	9.10^{-}	3.28
REFIN	737	0.90	0.30	1598	0.88	0.32	1853	0.68^{-}	0.47
REL	737	0.78	0.41	1598	0.67^{-}	0.47	1853	0.71^{-}	0.45
REVOLVER	737	0.82	0.38	1598	0.74^{-}	0.44	1853	0.40^{-}	0.49
ROA	737	0.06	0.06	1598	0.04^{-}	0.09	1853	0.00^{-}	0.15
SECURED	737	0.23	0.42	1598	0.79^{+}	0.40	1853	0.93^{+}	0.25
SPREAD	737	0.78	0.69	1598	1.73^{+}	0.96	1853	2.73^{+}	1.63
WCAP	737	0.08	0.13	1598	0.16^{+}	0.18	1853	0.11^{+}	0.20

Table 1 – *Panel B*: *Descriptive statistics of loan facilities in the FC period*

	Rating-based PP provision				Accounting-based PP provision				No PP provision			
Variable	**N**	**Mean**	**SD**	**Change**	**N**	**Mean**	**SD**	**Change**	**N**	**Mean**	**SD**	**Change**
FIRMSIZE	137	8.46	1.11	0.12	454	6.56^{-}	1.38	-0.01	502	6.89^{-}	1.83	-0.03
INTDEC	137	0.91	0.29	-0.02	454	0.79^{-}	0.41	-0.03	N/A	N/A	N/A	N/A
INTINC	137	0.93	0.25	0.03	454	0.67^{-}	0.47	0.06^{a}	N/A	N/A	N/A	N/A
LEV	137	0.32	0.16	0.03^{a}	454	0.20^{-}	0.19	-0.11^{ab}	502	0.39^{+}	0.38	-0.01
LOANSIZE	137	6.08	1.12	-0.25^{a}	454	4.64^{-}	1.18	-0.26^{a}	502	4.54^{-}	1.56	-0.29^{a}
MATURITY	137	3.32	0.74	-0.60^{a}	454	3.78^{+}	0.42	-0.23^{ab}	502	3.52^{+}	0.79	-0.46^{ab}
NUMOFAR	137	1.96	0.88	0.24^{a}	454	1.41^{-}	0.61	0.02^{b}	502	1.55^{-}	0.97	0.12^{a}
NUMOFCOV	137	1.43	0.78	-0.11	454	2.40^{+}	0.84	-0.07	502	1.46	1.33	0.24^{ab}
NUMOFLEN	137	13.38	8.58	-1.28	454	7.31^{-}	6.54	-0.98^{a}	502	4.74^{-}	5.72	-1.01^{a}
NUMOFSWEEPS	137	0.64	1.38	0.06	454	1.76^{+}	1.89	-0.52^{ab}	502	1.34^{+}	1.85	-0.11
RATING	118	12.76	2.59	0.05	120	9.67^{-}	2.08	0.82^{ab}	223	8.44^{-}	3.52	-0.66^{ab}
REFIN	137	0.66	0.48	-0.24^{a}	454	0.82^{+}	0.39	-0.06^{ab}	502	0.67	0.47	-0.01
REL	137	0.58	0.49	-0.20^{a}	454	0.61	0.49	-0.06^{ab}	502	0.56	0.50	-0.15^{ab}
REVOLVER	137	0.79	0.41	-0.03	454	0.71	0.45	-0.03	502	0.56^{-}	0.50	0.16^{ab}
ROA	137	0.04	0.06	-0.01^{a}	454	0.04	0.12	0.00	502	-0.04^{-}	0.20	-0.04^{a}
SECURED	137	0.27	0.45	0.04	454	0.76^{+}	0.43	-0.03	502	0.91^{+}	0.29	-0.02
SPREAD	137	2.05	1.29	1.27^{a}	454	2.52^{+}	1.14	0.79^{ab}	502	3.92^{+}	2.17	1.19^{a}
WCAP	137	0.06	0.15	-0.02	454	0.19^{+}	0.18	0.03^{ab}	502	0.10^{+}	0.33	-0.01

Table 1 – *Panel C*: *Descriptive statistics of loan facilities in the post-FC period*

	Rating-based PP provision				Accounting-based PP provision				No PP provision			
Variable	**N**	**Mean**	**SD**	**Change**	**N**	**Mean**	**SD**	**Change**	**N**	**Mean**	**SD**	**Change**
FIRMSIZE	372	8.57	1.17	0.23[a]	766	6.93[-]	1.27	0.36[a]	1498	7.30[-]	1.49	0.38[a]
INTDEC	372	0.97	0.18	0.04[a]	766	0.82[-]	0.38	0.00	N/A	N/A	N/A	N/A
INTINC	372	0.93	0.26	0.03	766	0.74[-]	0.44	0.13[ab]	N/A	N/A	N/A	N/A
LEV	372	0.29	0.13	0.00	766	0.28	0.23	-0.03[ab]	1498	0.38[+]	0.29	-0.02
LOANSIZE	372	6.41	0.99	0.08[a]	766	5.27[-]	1.14	0.37[ab]	1498	5.41[-]	1.29	0.58[ab]
MATURITY	372	3.83	0.46	-0.09[a]	766	4.00[+]	0.28	-0.01[b]	1498	4.00[+]	0.39	0.02[b]
NUMOFAR	372	3.39	1.80	1.67[a]	766	2.58[-]	1.73	1.19[ab]	1498	2.62[-]	1.85	1.19[ab]
NUMOFCOV	372	1.27	0.66	-0.27[a]	766	2.13[+]	0.85	-0.34[a]	1498	1.05[-]	1.18	-0.17[a]
NUMOFLEN	372	14.78	7.14	0.12	766	10.56[-]	9.00	2.27[ab]	1498	6.21[-]	4.99	0.46[a]
NUMOFSWEEPS	372	0.17	0.72	-0.41[a]	766	1.66[+]	1.86	-0.62[a]	1498	0.94[+]	1.66	-0.51[a]
RATING	331	13.13	1.86	0.42[a]	301	9.39[-]	1.74	0.54[a]	899	9.16[-]	2.81	0.06
REFIN	372	0.84	0.36	-0.06[a]	766	0.87	0.34	-0.01	1498	0.76[-]	0.42	0.08[ab]
REL	372	0.69	0.46	-0.09[a]	766	0.68	0.47	0.01[b]	1498	0.77[+]	0.42	0.06[ab]
REVOLVER	372	0.88	0.33	0.06[a]	766	0.70[-]	0.46	-0.04[ab]	1498	0.57[-]	0.5	0.17[ab]
ROA	372	0.05	0.05	-0.01[a]	766	0.04	0.11	0.00	1498	0.03[-]	0.12	0.03[a]
SECURED	372	0.12	0.33	-0.11[a]	766	0.75[+]	0.43	-0.04[ab]	1498	0.87[+]	0.34	-0.06[a]
SPREAD	372	1.68	0.70	0.90[a]	766	2.44[+]	0.95	0.71[ab]	1498	3.29[+]	1.75	0.56[ab]
WCAP	372	0.08	0.13	0.00	766	0.18[+]	0.18	0.02	1498	0.14[+]	0.18	0.03[a]

FC period includes loans with a loan start date between January 2008 and December 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively. The definitions of variables can be found in Appendix A.

Change is calculated as the change in variable mean from the pre-FC period to the FC (Panel B) and the post-FC period (Panel C). [a] superscript indicates whether these changes are statistically significant at 5%. [b] superscript indicates whether the *Change* for the subsample of loans with an accounting-based PP provision / no PP provision is significantly different from the *Change* for the subsample of loans with a rating trigger. When $^{+}$ ($^{-}$) superscript appears under "Mean" column, it indicates whether the variable mean for the subsample of loans with an accounting-based PP provision / no PP provision in a given period (i.e., pre-FC, FC, or post-FC) is significantly greater (smaller) at 5% than the variable mean for the subsample of loans with a rating trigger in that same period.

Table 2: *Structure of performance pricing grids*

		Rating-based PP provisions			Accounting-based PP provisions			
		Pre-FC	**Post-FC**	**Difference**	**Pre-FC**	**Post-FC**	**Difference**	**Difference-in-difference**
1.	*Number of levels in a pricing grid*	5.21	5.29	0.08	4.13	4.09	-0.04	0.12
2.	*Initial pricing grid level*	3.02	3.10	0.08	2.33	2.56	0.23[a]	-0.15
3.	*Immediate increase in loan spread when borrower's performance deteriorates*	14.66	22.04	7.38[a]	22.58	26.31	3.73[a]	3.65[a]
4.	*Immediate decrease in loan spread when borrower's performance improves*	11.82	19.72	7.90[a]	24.71	26.33	1.62[a]	6.28[a]
5.	*Average increase in loan spread when borrower's performance deteriorates (average of all levels)*	17.85	25.23	7.38[a]	23.69	26.96	3.27[a]	4.11[a]
6.	*Average decrease in loan spread when borrower's performance improves (average of all levels)*	10.61	18.41	7.80[a]	23.77	26.21	2.44[a]	5.36[a]
7.	*Maximum spread reduction obtainable through performance pricing*	22.19	38.56	16.37[a]	43.36	40.49	-2.87	19.24[a]
8.	*Maximum spread increase possible through performance pricing*	36.01	55.06	19.05[a]	30.92	40.87	9.95[a]	9.10[a]
9.	*Difference in loan spread between the highest and lowest level of pricing grid*	58.21	93.61	35.40[a]	74.28	81.36	7.08[a]	28.32[a]
10.	*Issuer rating at the time of loan initiation*	12.75	13.24	0.49[a]	8.87	9.44	0.57[a]	-0.08[a]

[a] denotes significance at 5%. All differences that are statistically significant at 5% are also significant at 1%.

Pre-FC period includes loans with a start date between January 2005 and December 2007. Post-FC period includes loans with a start date between January 2010 and December 2012. Difference-in-difference (column 7) is calculated as column 3 minus column 6. See Appendix C for an example of how the variables are calculated.

Table 3 - *Panel A*: *Relative use of rating triggers after the FC – full information maximum likelihood with sample selection*

Dependent variable	*BINRATTR*	*RATTR*	*PP*
Model	Base model (probit)	ML Probit with sample selection	Selection model
FC	-0.389***	-0.380***	0.026
	(-3.18)	(-3.26)	(0.54)
PostFC	-0.429***	-0.469***	-0.477***
	(-5.03)	(-5.91)	(-11.01)
MATURITY	-0.278***	-0.249***	0.150***
	(-2.99)	(-2.73)	(4.26)
SECURED	-1.252***	-1.318***	-0.787***
	(-12.44)	(-17.82)	(-17.59)
LOANSIZE	0.254***	0.271***	0.028
	(4.85)	(5.96)	(1.34)
REVOLVER	-0.077	-0.005	0.510***
	(-0.98)	(-0.07)	(13.10)
FIRMSIZE	0.399***	0.384***	-0.128***
	(7.05)	(9.80)	(-9.00)
LEV	0.273	0.205	-0.585***
	(1.15)	(1.11)	(-7.72)
ROA	-1.093*	-0.944*	1.231***
	(-1.82)	(-1.87)	(6.72)
RATING	0.110***	0.109***	-0.006
	(10.90)	(16.11)	(-1.59)
NUMOFLEN			0.060***
			(16.20)
NUMOFAR			-0.013
			(-0.92)
REFIN			0.515***
			(12.93)
REL			-0.119***
			(-2.87)
Industry fixed effects:	Yes	Yes	Yes
Rho		0.216**	
Observations	4178	8130	8130
Censored observations		3952	
Uncensored observations		4178	
Pseudo R^2	0.616		0.251

Table 3 - *Panel B*: *Relative use of rating triggers after the FC – multinomial logit model*

Base outcome	*No PP*		*Accounting-based PP*
Outcome	Accounting-based PP provision	Rating-based PP provision	Rating-based PP provision
FC	0.126	-0.310**	-0.436***
	(1.26)	(-1.96)	(-2.85)
PostFC	-0.743***	-1.302***	-0.558***
	(-8.90)	(-10.24)	(-4.43)
MATURITY	0.584***	0.223**	-0.361***
	(7.31)	(2.13)	(-3.93)
SECURED	-0.669***	-2.711***	-2.042***
	(-6.60)	(-17.93)	(-17.60)
LOANSIZE	0.227***	0.603***	0.376***
	(6.41)	(9.74)	(6.42)
REVOLVER	1.078***	0.807***	-0.271**
	(18.34)	(6.95)	(-2.33)
FIRMSIZE	-0.260***	0.161**	0.421***
	(-6.87)	(2.40)	(9.82)
LEV	-0.877***	-0.370	0.507**
	(-5.64)	(-1.17)	(2.31)
ROA	2.623***	1.118	-1.504**
	(6.86)	(1.38)	(-2.29)
RATING	-0.046***	0.105***	0.151***
	(-5.17)	(7.06)	(17.73)
Industry fixed effects:	Yes		
Observations	8130		
Pseudo R^2	0.312		

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics are provided in brackets.

FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. *PostFC* covers three years after the FC period.

BINRATTR equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision. *RATTR* equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision or no PP provision. *PP* takes the value of one if a loan contract includes any PP provision, and zero otherwise. All other variables are as defined in Appendix A.

In Panel A, regressions presented in columns 1 and 2 both have the same number of observations. The difference is that the second column also includes a correction for the selection bias, where the selection model is presented in column 3. In Panel B, column 3 is added for readers' convenience, and the coefficients from this column can easily be calculated as the coefficients from the second column minus the coefficients from the first column. The coefficients in Panel B are the logarithm of relative-risk ratios.

Table 4: *Relative use of rating triggers after the FC – sample selection based on the composition of borrowers in the pre-FC vs post-FC periods*

Dependent variable	*BINRATTR*		*STAYIN*
Model	Censored model w/out correction for SS bias	Censored model with correction for SS bias	Selection model
FC	-0.507***	-0.529***	
	(-3.18)	(-3.27)	
PostFC	-0.465***	-0.474***	
	(-4.60)	(-4.62)	
MATURITY	-0.258**	-0.232**	
	(-2.26)	(-2.05)	
SECURED	-1.323***	-1.266***	
	(-10.42)	(-8.95)	
LOANSIZE	0.197***	0.193***	
	(3.20)	(2.95)	
REVOLVER	-0.017	-0.029	
	(-0.18)	(-0.30)	
FIRMSIZE	0.455***	0.464***	0.178***
	(6.63)	(6.30)	(4.92)
LEV	0.595*	0.570*	0.033
	(1.87)	(1.76)	(0.16)
ROA	-1.170	-0.775	0.935**
	(-1.48)	(-0.95)	(2.12)
RATING	0.135***	0.137***	0.004
	(11.09)	(11.06)	(0.43)
CFTLIAB			-0.414**
			(-2.09)
CFTCURLIAB			0.143*
			(1.82)
CFTCAPEX			-0.019**
			(-2.46)
CFVOL			-1.791**
			(-2.36)
PUBDEBT			0.822***
			(7.87)
Industry fixed effects:	Yes	Yes	Yes
Rho		0.349	
Observations	2763	4255	4255
Censored observations		1492	
Uncensored observations		2763	
Pseudo R^2	0.631		0.175

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics are provided in brackets.
FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. *PostFC* covers three years after the FC period.
BINRATTR equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision. *STAYIN* equals one if the firm appears both in the pre-FC and the post-FC periods of the sample, and zero otherwise. All other variables are as defined in Appendix A. Regressions in columns 1 and 2 are restricted to firms that have borrowed in both the pre-FC and the post-FC periods. The difference between the two regressions is that the regression in column 2 also corrects for sample selection bias, where the selection model is presented in column 3.

Table 5 – *Panel A*: *The change in the use of rating triggers by investment banks vs commercial banks*

	INVBANK = 0	*INVBANK = 1*	Difference
	Prob (RATTR = 1 | PP = 1)		
Pre-FC	0.259	0.336	0.077***
FC	0.221	0.231	0.010
Post-FC	0.218	0.220	0.002
	Change from the pre-FC period		
FC	-0.038***	-0.105*	-0.067
Post-FC	-0.041***	-0.116***	-0.075**
Observations			8130
Censored observations			3952
Uncensored observations			4178
Industry fixed effects			Yes
Control variables			Yes

Table 5 – *Panel B*: *The change in the use of rating triggers by systemically important financial institutions vs other banks*

	SIFI = 0	*SIFI = 1*	Difference
	Prob (RATTR = 1 | PP = 1)		
Pre-FC	0.261	0.280	0.022
FC	0.203	0.215	-0.029
Post-FC	0.218	0.221	0.005
	Change from the pre-FC period		
FC	-0.058***	-0.051***	-0.008
Post-FC	-0.043**	-0.059***	-0.016
Observations			8130
Censored observations			3952
Uncensored observations			4178
Industry fixed effects			Yes
Control variables			Yes

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics provided in brackets.

FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively. The dependent variable in both panels is *RATTR*. *RATTR* equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision or no PP provision. *Prob (RATTR = 1 | PP = 1)* is the probability that a loan contract includes a rating trigger (conditional on *PP*) after controlling for loan and firm characteristics. *PP* takes the value of one if a loan contract includes any PP provision, and zero otherwise. Control variables are the same as in previous tables. See Appendix A for the definitions of control variables.

Prob (RATTR = 1 | PP = 1) is calculated from the output of a probit model that includes interactions between the *PostFC* (*FC*) and one of the main independent variables (*INVBANK* in Panel A and *SIFI* in Panel B). *INVBANK* equals one if at least one of the lead arrangers of the syndicate is identified as an investment bank, finance company, mutual fund, or pension fund in Dealscan, and zero otherwise. *SIFI* equals one if at least one of the lead arrangers was a systemically important financial institution during or immediately after the FC.

Table 6 – *Panel A*: *Rating quality and the change in the use of rating triggers*

	HIZSCORE = 0	*HIZSCORE = 1*	Difference	*HIPUBD = 0*	*HIPUBD = 1*	Difference
	Prob (RATTR = 1 | PP = 1)			*Prob (RATTR = 1 | PP = 1)*		
Pre-FC	0.394	0.449	0.043	0.280	0.316	0.036**
FC	0.385	0.338	-0.065	0.240	0.269	0.029
Post-FC	0.381	0.337	-0.042	0.211	0.287	0.076***
	Change from the pre-FC period			*Change from the pre-FC period*		
FC	-0.009	-0.111***	-0.102*	-0.040**	-0.047*	-0.007
Post-FC	-0.013	-0.112***	-0.099**	-0.069***	-0.029	0.040*
Observations			3452			6696
Censored observations			1669			3226
Uncensored observations			1783			3470
Industry fixed effects			Yes			Yes
Control variables			Yes			Yes

Table 6 – *Panel B*: *The change in the use of rating triggers across different capital structures*

	Number of debt types			
	1	**2**	**3**	**4**
	Prob (RATTR = 1 | PP = 1)			
Pre-FC	0.272	0.299	0.281	0.279
FC	0.274	0.230	0.240	0.249
Post-FC	0.192	0.220	0.253	0.259
	Change from the pre-FC period			
FC	0.002	-0.069**	-0.041*	-0.030
Post-FC	-0.080***	-0.079***	-0.028	-0.020
Observations				6696
Censored observations				3226
Uncensored observations				3470
Industry fixed effects				Yes
Control variables				Yes

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics provided in brackets.

FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively. The dependent variable in both panels is *RATTR. RATTR* equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision or no PP provision. *Prob (RATTR = 1 | PP = 1)* is the probability that a loan contract includes a rating trigger (conditional on *PP*) after controlling for loan and firm characteristics. *PP* takes the value of one if a loan contract includes any PP provision, and zero otherwise. Control variables are the same as in previous tables. See Appendix A for the definitions of control variables.

Prob (RATTR = 1 | PP = 1) is calculated from the output of a probit model that includes interactions between the *PostFC* (*FC*) and one of the main independent variables. The main independent variables are defined as follows. *HIZSCORE* equals one if the borrower's Z-score is higher than the median Z-score of borrowers within the same rating notch in a given fiscal year (Altman, 2000), and zero otherwise. *HIPUBD* equals one if 80% or more of the firm's debt comprises bonds and notes, and zero otherwise. The types of debt used in calculating the number of debt types are private debt (term loans and revolving lines), public debt (bonds and notes), capital leases, and other borrowings.

Table 7: *Loan spreads after the FC*

Dependent variable	*SPREAD*	
Model	Full model	*STAYIN = 1*
FC	1.069***	1.320***
	(15.00)	(14.67)
PostFC	0.852***	0.902***
	(17.35)	(15.55)
ACCTR	-0.268***	-0.193***
	(-4.65)	(-2.99)
RATTR	-0.176***	-0.060
	(-2.61)	(-0.78)
*ACCTR * FC*	-0.229**	-0.285***
	(-2.38)	(-2.61)
*RATTR * FC*	0.065	-0.158
	(0.48)	(-1.03)
*ACCTR * PostFC*	0.012	-0.018
	(0.20)	(-0.29)
*RATTR * PostFC*	0.137**	0.093
	(2.23)	(1.46)
MATURITY	0.102***	0.094***
	(3.32)	(3.08)
SECURED	0.609***	0.677***
	(19.62)	(14.55)
NUMOFLEN	-0.012***	-0.012***
	(-6.31)	(-5.98)
NUMOFAR	0.049***	0.048***
	(4.49)	(4.10)
LOANSIZE	-0.200***	-0.220***
	(-14.34)	(-14.39)
REVOLVER	-0.624***	-0.594***
	(-21.74)	(-15.60)
REFIN	-0.268***	-0.261***
	(-7.83)	(-5.92)
FIRMSIZE	0.027**	0.015
	(2.04)	(0.85)
LEV	0.351***	0.296***
	(5.29)	(3.44)
ROA	-2.401***	-2.572***
	(-14.97)	(-12.99)
RATING	-0.015***	-0.012***
	(-5.14)	(-3.63)

Table 7 *(continued):*

INTINC	-0.490***	-0.497***
	(-14.02)	(-12.82)
INTDEC	0.189***	0.190***
	(5.05)	(4.24)
NUMOFCOV	-0.069***	-0.049***
	(-4.79)	(-2.68)
NUMOFSWEEPS	0.091***	0.038***
	(11.30)	(3.39)
WCAP	-0.670***	-0.525***
	(-6.17)	(-3.65)
Industry fixed effects:	Yes	Yes
Observations	7916	5167
Adjusted R^2	0.534	0.575

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics provided in brackets.
FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. *PostFC* covers three years after the FC period.
RATTR equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision or no PP provision. *ACCTR* equals one if a loan contract includes an accounting-based PP provision, and zero if it includes a rating trigger or no PP provision. *SPREAD* is the loan spread over LIBOR, divided by 100. *STAYIN* equals one if the firm appears both in the pre-FC and the post-FC periods of the sample, and zero otherwise. All other variables are as defined in Appendix A. Regression in columns 2 is restricted to firms that have borrowed in both the pre-FC and the post-FC periods.

Table 8: *The change in loan spreads across different subsamples of borrowers*

Dependent variable	*SPREAD*	
PostFC	0.856***	1.229***
	(23.30)	(17.77)
BINRATTR	-0.038	0.158**
	(-0.90)	(2.38)
*PostFC * BINRATTR*	0.090	-0.074
	(1.22)	(-0.86)
HIPUBD	0.023	
	(0.59)	
*BINRATTR * HIPUBD*	-0.072	
	(-1.46)	
*PostFC * HIPUBD*	0.380***	
	(4.70)	
*PostFC * BINRATTR * HIPUBD*	-0.274**	
	(-2.35)	
HIZSCORE		0.093
		(1.55)
*BINRATTR * HIZSCORE*		-0.091
		(-1.38)
*PostFC * HIZSCORE*		-0.198***
		(-2.61)
*PostFC * BINRATTR * HIZSCORE*		0.095
		(0.91)
Industry fixed effects:	Yes	Yes
Control variables	Yes	Yes
Observations	2883	1586
Adjusted R^2	0.694	0.775

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. Z-statistics provided in brackets.
FC denotes the financial crisis period and takes the value of one if the loan start date is between January 2008 and December 2009. *PostFC* covers three years after the FC period.
RATTR equals one if a loan contract includes a rating trigger, and zero if it includes an accounting-based PP provision or no PP provision. *ACCTR* equals one if a loan contract includes an accounting-based PP provision, and zero if it includes a rating trigger or no PP provision. *SPREAD* is the loan spread over LIBOR, divided by 100. *HIZSCORE* equals one if the borrower's Z-score is higher than the median Z-score of borrowers within the same rating notch in a given fiscal year (Altman, 2000), and zero otherwise. *HIPUBD* equals one if 80% or more of the firm's debt comprises bonds and notes, and zero otherwise.

Chapter 4

Rating quality and firms' reporting quality

Abstract

Stronger market reactions to rating movements due to more informative ratings is expected to give rated firms stronger incentives to avoid the potentially negative consequences of lower rating inflation (i.e., potential downgrades). Accordingly, this chapter examines whether rated firms engage in misreporting to influence their ratings in response to an increase in rating quality. I find that accrual-based earnings management increased in rated firms, but not in non-rated firms, in the post-FC period. Results indicate this increase is mainly driven by firms with strong rating-related incentives (i.e., firms with rating triggers). In tests motivated by CRAs' adjustments to firms' operating income, I also find that firms with investment grade threshold ratings and minus-notch ratings manage financial numbers that feed into these adjustments to a greater extent in the post-FC period. Since rating quality is significantly affected by the quality of information used in the rating process, this study informs regulators on the adverse effects of regulatory reforms intended to improve overall rating quality.

4.1 Introduction

Credit ratings play an important role in firms' access to capital markets. They significantly affect public debt investors' and investment managers' investment decisions as well as private lenders' lending decisions (Cantor, Gwilym, & Thomas, 2007; Hand et al., 1992). Since ratings provide markets with incremental information about firms' and individual issues' creditworthiness, an increase in the quality of ratings is expected to strengthen the market participants' (lenders' and investors' alike) reaction to rating changes.[41] This, in turn, is likely to give firms strong incentives to influence their ratings in order to avoid the potential downgrades that may result from tighter rating standards.[42] Despite the implications of a change in rating quality for rated firms, however, we still know little about how firms respond to such a change.

Considering that the information used by CRAs in the rating process mainly comes from financial statements, one way firms can influence their ratings is by manipulating the information contained in the financial statements. In most cases, this involves managing earnings to boost the reported income because, given that a firm's ability to pay off its debt strongly depends on its cash flows, CRAs pay additional attention to the net cash inflow figure. Prior research finds that firms can successfully use accrual-based EM and earnings smoothing to manage the CRAs' perception of their credit risk (Alissa et al., 2013; Jung et al., 2013; Liu et al., 2018). Taking into account this evidence, and the theoretical predictions that a change in rating quality may affect firms'

[41] For evidence on how an increase in rating quality affects the extent to which rating changes move interest rates and bond prices, see Chapter 3, Jankowitsch et al. (2017), and Badoer et al. (2019).

[42] Conceptually, higher rating assessment quality may result in a better distinction between the high quality and low quality issuers (i.e., increase in the precision of ratings), leading to some ratings being upgraded without any improvements in underlying credit risk. When developing hypotheses, however, I focus only on the negative consequences of higher rating quality for firms because (i) firms do not have any incentives to influence their ratings if their ratings are to be upgraded, and (ii) significantly higher number of ratings are likely to be downgraded than to be upgraded due to lower rating inflation (as shown in prior studies), making the consequences of higher rating quality negative on average.

misreporting behavior (discussed below), this chapter investigates whether an increase in rating quality leads to changes in rated firms' reporting quality.

Two theoretical studies provide guidance on how firms are likely to change their misreporting behavior in response to a change in rating quality. Cohn et al. (2018) construct a model where firms can distort the information used to rate securities when CRAs change their screening intensity. The main prediction of the model is that when the initial screening intensity is low (high), an increase in screening intensity – and hence, in rating quality – prompts low quality issuers to increase (reduce) misreporting because manipulation has a high (low) chance to succeed in a low (high) screening intensity state.[43] Lee and Schantl (2019) model a setting where the level of rating inflation and the issuer's reporting quality interact endogenously. An increase in rating inflation costs leads to a reduction in rating inflation, making a favorable rating more valuable for the issuer. How the issuer reacts to a decrease in rating inflation then depends on the CRAs' role in financial markets. In a regime where CRAs are not gatekeepers or lose their gatekeeper status, a decrease in rating inflation strengthens the issuer's incentives to misreport. When CRAs act as gatekeepers, however, reducing rating inflating dampens the issuer's incentives to misreport and hence leads to higher reporting quality.[44]

Considering that a common investment policy followed by the majority of institutional investors is to invest in only the investment grade securities, CRAs' gatekeeper role arises when the issuer's or issue's credit quality is at the investment grade threshold.[45] Due to the higher reputational costs of assigning inaccurate ratings to

[43] This prediction holds at moderate manipulation costs.
[44] This result is conditional on that accounting quality is sufficiently high.
[45] Despite the elimination of regulatory references to ratings from federal laws following the FC, many state laws and internal policies of institutional investors still prevent investment managers from investing in speculative grade securities (Partnoy, 2017).

issues/issuers at this threshold, CRAs are also likely to exert more due diligence in rating and monitoring such issuers (Kraft, 2015a), especially in the face of regulatory and public criticisms. Consequently, based on the predictions of Lee and Schantl (2019) and relevant empirical evidence, I hypothesize that firms with an investment grade threshold rating improve their reporting quality in response to an increase in rating quality. Firms with a minus-notch rating (e.g., AA-, A- etc) are likely to respond similarly because CRAs' scrutiny of these firms tends to be stronger due to their importance for market participants (Jung et al., 2013). In light of the theoretical guidance, I expect the remaining rated firms to increase misreporting in response to increased rating quality.

To test these hypotheses, I compare the changes in non-rated firms' reporting quality from the pre-FC to the post-FC period to that of rated firms, firms with investment grade ratings, and firms with minus-notch ratings. I explore two earnings management proxies to capture misreporting. The first one, commonly used as a proxy for accrual-based EM in prior research, is the abnormal accruals obtained from Jones (1991) model that is further modified based on follow-up studies (see subsection 4.3.2 for more details). Results from abnormal accruals tests suggest that in the pre-FC period rated firms had, on average, similar levels of abnormal accruals as non-rated firms. More importantly, and consistent with the theoretical predictions, while results indicate an increase in abnormal accruals in rated firms in the post-FC period, no such increase is documented for non-rated firms. These findings are robust to controlling for the possibly different credit quality of rated and non-rated firms in the post-crisis period stemming from a change in the borrowing environment after the crisis (McKinsey & Co., 2018).

To address the possibility that these results are driven by changes in certain firm characteristics specific to rated firms and which are unaccounted for in multivariate tests, I identify two subsets of rated firms that are likely to have stronger rating-related

incentives and examine if the increase in abnormal accruals was stronger in these firms. I use the placement of the firm under negative credit watch and the presence of a debt contract with a rating trigger to proxy for high rating-related incentives. The rationale behind the first proxy is rather straightforward as a negative credit watch is often a precursor to a rating downgrade. Having a debt whose performance is tied to a credit rating means that a rating downgrade will immediately increase the firm's cost of debt, giving the firm strong incentives to avoid downgrades. Moreover, as documented in Chapter 3, performance pricing grids specify bigger changes in loan spreads in response to rating movements in the post-FC period than in the pre-FC period, further strengthening firms' rating-related incentives. Results from the tests performed on these subsets of rated firms suggest that the increase in accrual-based EM documented earlier is mainly driven by firms with rating triggers. This increase is not statistically different between firms placed under negative credit watch and other rated firms, however.

Next, I examine whether firms with investment grade threshold ratings or minus-notch ratings manage accruals less in response to an increase in rating quality. I find that before the FC, firms at the investment grade threshold had higher abnormal accruals than non-rated and other rated firms. However, inconsistent with the predictions, the change in the abnormal accruals of these firms from the pre-FC to the post-FC period was not statistically distinguishable from zero. Tests on the subsample of firms with minus-notch ratings provide similar inferences.

The second EM proxy used in the study is based on S&P's rating methodologies. When assessing a firm's financial risk, rating agencies make numerous adjustments to debt and income figures to improve the comparability and consistency of rating analyses

across firms and security classes.[46] Therefore, to influence the CRA's assessment of their financial risk, firms can manage the specific financial numbers (predominantly accruals) that feed into the CRA's adjustments to reported earnings. To capture such earnings management, I develop an empirical proxy that comprises financial numbers used in these adjustments as disclosed in S&P's 2008 Corporate Criteria (see subsection 4.3.3 for further details). I assume that, controlling for other relevant factors, an increase in this metric is evidence of the firm's attempt at boosting the measure of earnings used by CRAs in the rating process (i.e., the earnings number calculated by CRAs through adjustments to operating income). One advantage of this EM proxy over more traditional accrual-based EM measures is that the findings from these tests can be more readily attributed to changing rating standards as these adjustments are specific to the rating process.

Results from the tests employing this metric provide several interesting insights. Consistent with rated firms managing the financial numbers important for the rating process, operating income adjustments (i.e., the sum of financial numbers used in adjusting operating income) was higher in rated firms than in non-rated firms in both the pre-FC and the post-FC periods. Consistent with the findings from Kraft (2015a), the magnitude of these adjustments was greater in firms with rating triggers than in other rated firms. More importantly, results indicate that the aggregate of financial numbers used by CRAs in adjusting operating income increased in the post-FC period in rated firms, but not in non-rated firms. This increase is driven by firms that face stronger CRA monitoring (i.e., firms with investment grade threshold ratings or minus-notch ratings), likely because such targeted earnings management is arguably harder to detect. The reason is that the list of financial numbers involved in the adjustment process is rather lengthy, so even small changes to some of these numbers may add up and make a

[46] For more details on ratios and adjustments, see S&P (2013b).

difference for the rating assessment. Taken together, these results support the earlier findings that rated firms are likely to increase misreporting when CRAs tighten their rating standards and reduce rating inflation.

This chapter contributes primarily to the rating quality literature. Prior studies in this stream of literature have almost exclusively focused on the impact of regulatory changes, reputational shocks, and other factors on CRAs' behavior and rating quality (discussed earlier). Unlike prior studies, this chapter explores *firms'* responses to a change in rating standards, and finds that an improvement in rating standards leads to lower reporting quality. An important implication of this finding is that since rating quality is a product of the quality of rating assessment and the quality of information used in the rating process, an improvement in rating standards may not translate into the same level of increase in rating quality. Consequently, this study informs regulators and interested parties on the inadvertent outcomes of regulatory changes that aim to improve overall rating quality. Additionally, it highlights a previously unexplored dimension of earnings management firms may use to influence their ratings and introduces a way of calculating an empirical measure for it using publicly available data.

The rest of the chapter is structured as follows. Section 4.2 discusses the related literature and develops hypotheses. Section 4.3 provides an outline of the research design. Section 4.4 discusses the sample selection procedure and descriptive statistics. Section 4.5 discusses results from multivariate tests. Section 4.6 concludes.

4.2 Hypothesis development

4.2.1 Firms' rating related incentives

There are several reasons why higher rating quality could lead to a change in firm behavior. First, credit ratings are one of the two most important factors affecting firms'

debt policy (Graham & Harvey, 2001). They are a significant determinant of firms' cost of debt and are frequently used as guidance in investment decisions (Cantor et al., 2007). Therefore, firms have incentives to take steps to prevent the potentially negative consequences of higher rating quality (deHaan, 2017; Dimitrov et al., 2015; S&P, 2009). Second, rating movements trigger a significant investor reaction in equity and debt markets (Asquith et al., 2005; Hand et al., 1992). Since higher rating quality implies more informative ratings, market reaction to rating changes is expected to be stronger in the post-FC period than in the pre-FC period. Two pieces of evidence support this prediction. Jankowitsch et al. (2017) find that corporate bond investors react to rating movements more strongly following the changes to regulations pertaining to CRAs in the wake of the FC. Results from Chapter 3 suggest that rating downgrades and upgrades lead to bigger loan spread movements after the FC.

Similarly, a rating change (or lack thereof) following an improvement in rating quality may act as a signal to the market about the firm's credit risk. Using Moody's refinement of its rating symbols in 1982, Kliger and Sarig (2000) find that investors reacted significantly when Moody's announced better- or worse-than-expected ratings.[47] Using the same setting, Tang (2009) provides evidence that firms with rating downgrades (upgrades) as a result of this refinement experienced an additional increase (decrease) in their ex-post borrowing costs. To the extent that higher rating quality improves the precision of information communicated through ratings, a rating downgrade following an increase in rating quality may constitute a bad signal to the market and have undesired consequences for the firm, thus providing it with strong incentives to respond to tighter rating standards.

[47] In 1982, Moody's increased the number of its rating symbols from 9 to 19 – an event that led to a rating action for all bonds without any fundamental change in issuers' risks.

4.2.2 The relationship between rating quality and firms' reporting quality

Given the rating agencies' dependence on fee revenues from issuers and the importance of ratings for firms, the quality of CRAs' rating assessment is likely to be endogenously determined in relation to the issuer's reporting quality. Two theoretical studies take this relationship into consideration, but they differ in how they model it. Cohn et al. (2018) examine how the CRAs' screening intensity affects the issuer's incentives to manipulate the information provided to CRAs. The main predictions of the model are driven by how the issuers of low quality securities (low type issuers) behave in response to a change in CRA screening intensity. When the cost of inaccurate ratings increases, CRAs improve their screening intensity. At moderate manipulation costs, this leads to more misreporting by low type issuers when the initial screening intensity is low, and less misreporting when the initial screening intensity is high. The initial level of screening intensity significantly affects the issuer's misreporting behavior because the probability that manipulation succeeds differs in low versus high screening intensity states. Therefore, in order to make a directional hypothesis regarding the change in rated firms' reporting quality in the post-FC period, one must make an assumption about the pre-FC level of issuer rating quality.

Lee and Schantl (2019) examine how the level of rating inflation and the issuer's reporting quality interact endogenously. Two sets of predictions from their study are relevant to this chapter's research question. First, under imperfect industry competition, CRAs reduce rating inflation when the cost of inflating ratings increases, making a favorable rating more valuable for issuers. This, in turn, strengthens issuers' incentives to misreport and leads to more issuer misreporting. The prediction that an increase in rating inflation costs leads to lower reporting quality holds when CRAs do not assume a gatekeeper role in financial markets or lose their gatekeeper status. In a regime where

CRAs act as gatekeepers, however, rating inflation and reporting quality may also be complements. In this scenario, provided that the issuer's accounting quality is sufficiently high, increased rating inflation costs (and lower rating inflation) will thus lead to *higher* reporting quality. This is because when the likelihood of project financing depends on providing investors with a favorable rating from CRAs, lower rating inflation reduces the probability that the project will be financed, hence weakening the issuer's incentives to misreport.

It is not clear to what extent the CRAs' gatekeeper status has changed since the FC. On the one hand, the SEC has eliminated regulatory references to credit ratings from federal laws as mandated by Dodd-Frank, and investors are more cautious about using ratings in investment decisions (more details provided in Chapter 2). On the other hand, internal policies of most institutional investors and laws in many states still rely on credit ratings (Partnoy, 2017). Since the most common investment guideline institutional investors follow is to invest in only the investment grade securities, CRAs' gatekeeper role manifests itself most strongly at the investment grade threshold. For this reason, CRAs have higher than usual reputation costs (i.e., higher cost of issuing inaccurate ratings) at the investment grade threshold (Kraft, 2015a). Due to higher reputational costs, CRAs are also likely to exert more due diligence during the rating process, and have stronger monitoring of these firms after assigning the rating.

Another case where firms are expected to face stronger CRA monitoring is when they have a minus-notch rating (ratings such as AA-, BBB- etc). Jung et al. (2013) find that markets react more strongly when a downgrade results in a change in the broader rating category, i.e. when a minus-notch rating is downgraded. Given their importance for market participants, minus-notch firms are downgraded in a significantly more timely manner as well (Jung et al., 2013). Therefore, in light of the theoretical predictions and

empirical evidence discussed in this section, I expect firms with an investment grade threshold rating or a minus-notch rating to reduce, and other rated firms to increase, misreporting in response to an increase in rating quality.

H1a: *Reporting quality declines in rated firms in response to an increase in rating quality*.

H1b: *The decline in reporting quality in response to an increase in rating quality is stronger in firms with high rating-related incentives*.

H2a: *Reporting quality improves in firms at the investment grade threshold in response to an increase in rating quality*.

H2b: *Reporting quality improves in firms with minus-notch ratings in response to an increase in rating quality*.

4.3 Research design

4.3.1 Empirical strategy and the variables of interest

I use the changes in rating standards in the wake of the FC as the main setting to test the study's hypotheses. The pre-FC, FC, and post-FC periods are defined as in Chapter 3. The FC period spans from January 2008 to December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the *FC* period, respectively. The following empirical models (time and firm subscripts have been suppressed) are used to test H1a (equations 1) and H1b (equation 2):

$$EM = \gamma_0 + \gamma_1 RATED + \gamma_2 PostFC + \gamma_3 RATED * PostFC + \gamma_4 FC + \gamma_5 RATED * FC + \sum \gamma_i Controls + \varepsilon \quad (1)$$

$$EM = \rho_0 + \rho_1 RATED + \rho_2 HRINC + \rho_3 PostFC + \rho_4 RATED * PostFC + \rho_5 HRINC * PostFC + \rho_6 FC + \rho_7 RATED * FC + \rho_8 HRINC * FC + \sum \rho_i Controls + \epsilon \quad (2)$$

where *EM* refers to the two earnings management proxies used to capture the changes in reporting quality.

One of these measures, abnormal accruals obtained from a version of Jones (1991) model, is commonly used as an accrual-based EM proxy in the credit ratings literature. Using this proxy, Alissa et al. (2013) and Liu et al. (2018) find that accrual-based EM helps firms to obtain their "target" rating and avoid a downgrade when placed under negative credit watch, respectively. In a related study, Jung et al. (2013) document a positive relationship between the change in earnings smoothness and the likelihood of a subsequent rating upgrade for firms with plus-notch ratings. One caveat of using abnormal accruals in this study's setting is that, under certain conditions, the significance and the sign of the coefficient on *RATED∗PostFC* (equation 1) may be driven by factors other than rating-related incentives. This is likely to be the case if rated and non-rated firms have different characteristics and the changes in discretionary accruals caused by the FC are significantly associated with these characteristics.[48] Consequently, I develop another EM proxy based on S&P's rating criteria to use in conjunction with discretionary accruals (see subsection 4.3.3).

From the main independent variables, *RATED* is a binary variable that equals one if a firm had an issuer rating from S&P or Moody's in a given fiscal year, and zero otherwise.[49] A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *HRINC* refers to firms that are expected to have strong rating-related incentives. Based on the findings from prior literature, I

[48] Note that is less likely when *HRINC* and its interactions are included in equation 2 as discussed below. Additionally, a number of control variables are included to at least partially overcome this problem. See subsection 4.3.4 for more details.
[49] When a firm has an issuer rating from both S&P and Moody's, I use S&P's issuer rating. When a firm is not rated by S&P, I manually look up whether the firm has an issuer rating from Moody's and use it in tests.

identify two sets of firms with such incentives. *RTR* refers to firms that, at the end of the fiscal year, had at least one private debt contract that included a rating trigger. Since such debt contracts directly tie a loan's interest rate to the borrower's credit rating, the effect of a rating change on the firm's cost of borrowing is immediate, making a rating movement an especially important event for the firm. CRAs pay additional attention to debt contracts with rating triggers because "triggers can change minor adversity into a major crisis for the company" and thus, are not viewed favorably by rating agencies (S&P, 2008a). Moreover, findings from Chapter 3 suggest that rating changes have a more significant impact on loan spreads through pricing grids in the post-FC period than in the pre-FC period, further strengthening the incentives of firms with rating triggers to avoid downgrades or obtain upgrades.

CWNEG equals one if the firm was placed under credit watch at least once during the fiscal year, and zero otherwise. These firms are expected to have strong rating-related incentives due to the fact that a negative credit watch is often a forerunner of a rating downgrade. Evidence suggests that performance-matched discretionary accruals reported during negative credit watch are significantly higher than their respective pre- and post-watch levels (Liu et al., 2018). Such accrual management also significantly reduces the likelihood that the rating will be downgraded when the credit watch resolves.

Since both *RTR* and *CWNEG* are subsets of *RATED*, their interactions with *RATED* do not appear separately in the equations. Thus, to be able to compare the changes in EM from the pre-FC to the post-FC period between *RTR* (*CWNEG*) firms and non-rated firms, one needs to sum the coefficients on *PostFC∗RATED* and *PostFC∗RTR* (*PostFC∗CWNEG).*

I use the following empirical models (time and firm subscripts have been suppressed) to test H2a (equations 3) and H2b (equation 4):

$$EM = \beta_0 + \beta_1 RATED + \beta_2 IGT + \beta_3 PostFC + \beta_4 RATED * PostFC + \beta_5 IGT * PostFC + \beta_6 FC + \beta_7 RATED * FC + \beta_8 IGT * FC + \sum \beta_i Controls + \epsilon \quad (3)$$

$$EM = \alpha_0 + \beta_1 RATED + \alpha_2 MNOTCH + \alpha_3 PostFC + \alpha_4 RATED * PostFC + \alpha_5 MNOTCH * PostFC + \alpha_6 FC + \alpha_7 RATED * FC + \alpha_8 MNOTCH * FC + \sum \alpha_i Controls + \epsilon \quad (4)$$

IGT is an indicator for firms that are at the investment grade threshold and have either the S&P (Moody's) issuer rating of BBB- (Baa3), the lowest investment grade rating, or BB+ (Ba1), the highest non-investment grade rating. *MNOTCH* (minus-notch) refers to firms that have an issuer rating of AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, or B3) from S&P (Moody's). Since both *IGT* and *MNOTCH* are subsets of *RATED*, their interactions with *RATED* do not appear separately in the equations.

4.3.2 Empirical measure of discretionary accruals

The other proxy for accrual-based EM, discretionary or abnormal accruals (*ABACC*), is obtained by estimating equation 5 for each industry-year and performance-matching the residuals from these regressions as per Kothari, Leone, and Wasley (2005).[50] The accruals model is based on Jones (1991) and Dechow, Sloan, and Sweeney (1995), but also includes a constant term as per Kothari et al. (2005), lagged total accruals as per

[50] Each industry-year group is required to have at least 12 observations. I use two-digit SIC codes to determine industries. Performance-matching is done by identifying the firm with the closest ROA within the same industry-year and differencing the abnormal accruals of the two firms.

Louis, Robinson, and Sbaraglia (2008), and *Idioshock* variable as per Owens, Joanna Shuang, and Zimmerman (2017):

$$TA_{it}/A_{it-1} = \alpha_0 + \alpha_1(1/A_{it-1}) + \alpha_2(\Delta S_{it}/A_{it-1}) + \alpha_3(PPE_{it}/A_{it-1}) + \alpha_4 TA_{it-1}/A_{it-2} + \alpha_5 Idioshock_{it} + \epsilon_{it} \quad (5)$$

In equation 5, *TA* refers to total accruals. *A* refers to total assets. Δ*S* is the change in sales from last year. *PPE* is property, plant, and equipment. Following Hribar and Collins (2002), total accruals are calculated as income before extraordinary items and discontinued operations minus operating cash flows from continuing operations. Following Owens et al. (2017), *Idioshock* is calculated as the mean of squared residuals from a regression of the firm's monthly stock returns on value-weighted industry and market returns (24-months window regressions). The inclusion of this variable intends to accommodate (albeit only partially) for the fact that firms in the same industry experience idiosyncratic shocks due to different economic fundamentals and hence have different accrual-generating processes. Owens et al. (2017) show that including this variable in accrual models can improve the models' fit.

4.3.3 Developing a proxy for EM by using credit rating methodologies

4.3.3.1 CRAs' adjustments to firms' operating income

Credit rating assessment usually starts with an assessment of the company's business risk and financial risk.[51] Business risk assessment incorporates the impact of country risk, industry risk, and the company's competitiveness on ratings using both qualitative and quantitative information. Financial risk analysis involves assessing the

[51] The discussion in this section is motivated by S&P's corporate rating methodologies. However, the analyses performed by CRAs are fairly similar when it comes to general factors considered important for the rating assessment (the main differences usually lie in specific assumptions). Therefore, the discussion in this section is easily generalizable to other rating agencies.

company's expected cash flows relative to its leverage using a host of financial ratios and other quantitative information. Factors such as capital structure considerations, financial policy, liquidity, and governance are then used as the modifiers to the initial assessment of the company's creditworthiness (for a more detailed discussion, see S&P (2013b) corporate rating methodology).

During financial risk assessment, CRAs make numerous adjustments to earnings, cash flows, and debt figures when calculating financial ratios. The first and foremost reason for doing so is the fact that accounting standards provide the preparers different options for the treatment of certain items. Second, as business transactions and related accounting rules become more complex, companies increasingly use more subjective estimates and judgments. Third, the current accounting treatment of certain debt-like items could reduce the quality of the information presented in financial statements (S&P, 2013a). The adjustments made by CRAs thus aim to enhance the consistency and comparability of financial analyses among companies. In many cases, these adjustments can be quite sizeable. For example, Kraft (2015b) finds that Moody's adjusted coverage (cash flow-to-debt) ratios are 27 percent (8 percent) lower and adjusted leverage ratios are 70 percent higher than the corresponding U.S. GAAP ratios.

Firms are knowledgeable about the type and the extent of these adjustments. They not only can access the information about the adjustments on CRAs' websites, but can also enquire of the CRAs about the potential impact of these adjustments on their ratings. In its corporate rating methodology, S&P even "encourage[s] companies to discuss hypothetically transactions that perhaps are only being contemplated … to provide frank feedback about the potential ratings implications of such transactions" (S&P, 2006). Therefore, to get a better financial risk assessment from CRAs, firms can manage the

financial numbers that feed into the CRAs' adjustments to firms' earnings (i.e., manage the earnings number that is calculated by CRAs for use in rating assessment).

4.3.3.2 Empirical measure of operating income adjustments

To examine the change in the extent to which firms manage the earnings number used in the CRAs' financial risk analysis, I develop an empirical proxy (*OPINCADJ*) to capture the difference between the operating income number disclosed by the firm and the adjusted operating income figure. Consequently, *OPINDACJ* is a measure of the CRAs' adjustments to a firm's operating income. I assume that, controlling for other factors, a significant increase in *OPINCADJ* is evidence of a firm's attempt at managing the measure of earnings used in the rating process. An important advantage of examining the adjustments to operating income over the tests using more traditional EM proxies is that the documented results can be more readily attributed to a change in rating quality as the adjustments are specific to the rating process.

I follow S&P's 2008 Corporate Criteria as closely as possible to calculate *OPINCADJ*, but some of the financial numbers cannot be adjusted either due to the unavailability of data from Compustat or because the adjustment would require private information from managers.[52] These items include, but are not limited to, exploration costs for oil and gas exploration and production companies that use full cost accounting method, non-recurring foreign currency exchange gains and losses, as well as adjustments due to power purchase agreements, asset retirement obligations, and stranded costs securitizations of regulated industries. The operating income adjustment is calculated as deferred income taxes, minus income taxes, minus capitalized software costs, minus

[52] Applying the same criteria to observations both before and after the crisis ensures that the documented results are due to a change in firm behavior, not due to a different CRA methodology. In any case, these adjustments are very similar to those discussed in 2006 Corporate Rating Criteria.

capitalized interest, minus finance division's income (finance division's revenue minus finance division's operating expense), minus 50% of preferred dividends, minus write-downs after tax for the retail industry, plus adjustment due to operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment, plus/minus adjustment due to the use of LIFO.[53] *OPINCADJ* is then obtained by dividing the operating income adjustment by sales.

Since write-downs are considered a normal part of doing business for the retail industry, they are considered as operating expenses and hence, deducted from income. 50% of preferred dividends are deducted from operating income because of the hybrid nature of preferred shares, i.e., half of preferred dividends are considered to be an interest-like expense. The post-retirement adjustment represents the adjustment to eliminate the inclusion of all post-retirement charges/credits that are part of net periodic post-retirement costs. Core pension adjustment represents the after-tax adjustment to net income for the company's core earnings calculation. Core post-retirement adjustment and core pension adjustment are readily available from Compustat, but can also be calculated by following S&P's rating methodology on pension adjustments. The depreciation portion of operating leases is calculated as the rent expense, minus the discount rate multiplied by the average of minimum rental commitments (1st year) for the current year and the previous year. I use the implied interest rate (calculated as interest expense divided by total debt) as the discount rate. Since the choice of inventory method can significantly affect profits, S&P deducts LIFO liquidation gains from operating income. However, as data on liquidation

[53] To enhance comparability, rating agencies have long treated operating and capital leases in the same way despite the differential accounting treatment of the two in the US. Consequently, S&P divides operating leases into depreciation and interest portions and deducts only the interest portion from operating income (i.e. by adding back the depreciation portion of operating leases).

gains is not available, I assume that a reduction in LIFO reserves is a sign of liquidation gains and hence, use the decrease in LIFO reserves as a proxy for LIFO liquidation gains.

4.3.4 Control variables and other empirical considerations

The choice of control variables is motivated by prior literature (e.g., see Alissa et al., 2013). I include five variables to control for firm characteristics. *LEV* is the sum of short- and long-term debt divided by total assets. *SIZE* is the natural log of total assets. *GROWTH* is the percentage change in sales from year t-2 to year t-1. *MTB* is the firm's market-to-book ratio and is calculated as the book value of assets, less the book value of equity, plus the market value of equity, divided by assets (measured in t-1). *RATING* is the firm's issuer rating expressed in terms of integers, where 21 refers to AAA rating and 1 refers to default (D rating).[54] It takes the value of zero if a firm does not have an issuer rating. I include *NEGNI* to control for firms' performance-related incentives to manage earnings. It is an indicator variable that equals one if the firm had negative earnings for the last two or more years, and zero otherwise.

I also include variables to control for the change in earnings management due to governance-related issues and scrutiny from other parties. *INDPERC* is the percentage of independent directors on the board. *CHAIR* is an indicator variable that equals one if the firm's CEO is also the chair of the board, and zero otherwise. *INST* is the percentage of institutional holders. *ANAFOL* is the number of equity analysts following the firm.

One potential problem with using the financial crisis as the main setting is that, in parallel to the changes in rating standards from the pre-FC to the post-FC period, the borrowing environment changed as well. Specifically, banks became more selective in

[54] Appendix B provides a table specifying the numbers corresponding to each issuer rating from S&P and Moody's.

terms of the borrowers to whom they were willing to lend, and more (lower quality) firms started raising capital from the public after the FC (McKinsey & Co., 2018). Given that firms issuing public debt almost always obtain a credit rating, and that one of the main independent variables in this study is whether a firm has a credit rating, certain test results may be driven not by rating-related incentives but by other debt-related incentives stemming from the different lending environment after the FC. It is worth noting that this issue becomes less problematic when more specific subsamples such as *RTR* or *CWNEG* firms are examined because these firms have stronger rating-related incentives and findings are less likely to be attributable to other factors.

Since I am unable to use the common credit quality proxies such as credit ratings or bond yields to control for the changes in the borrowing environment, I include variables that are expected to affect the probability and/or the cost of external financing (in addition to the existing control variables).[55] *ZSCORE* refers to the modified version of Altman's Z-score and is intended to control for the possibly different default probabilities of firms in the post-FC period (Altman, 2000). *WCAP* is working capital divided by total assets and is intended to control for firms' short-term liquidity. *CFVOL* is the standard deviation of the firm's cash flows for the last ten years and is intended to control for firms' cash flow volatility. Cash flows is calculated as operating income before depreciation and amortization minus interest, taxes, and dividends, divided by total assets. *ROE* is calculated as net income divided by total assets. *CFTLIAB* is the ratio of operating income before depreciation and amortization to liabilities. *CFTCAPEX* is the ratio of net cash flows from operating activities to capital expenditures.[56] Additionally, *EXTFIN* is

[55] The reason why bond yields cannot be used for this purpose is because they are available only for firms issuing bonds, which are also predominantly the firms that have a credit rating. Restricting the sample to firms for which bond yields data is available would thus severely bias the sample.
[56] As in Chapter 3, the choice of these three ratios is motivated by S&P's rating methodologies (S&P, 2008b).

included to control for firms' incentives to manage earnings when they are under financial distress. It equals one if the firm's free cash flow is less than -0.5, and zero otherwise.[57] The definitions of all variables are also presented in Appendix A and Appendix I.

Since coefficients and t-statistics are biased when the dependent variable comprises residuals from another regression (which is the case for *ABACC*), I correct for this bias using one of the methods suggested by Chen, Hribar, and Melessa (2018). This method involves regressing each of the right-hand side variables from the second stage on the set of right-hand side variables from the first stage and using the residuals obtained from this regression in the second stage instead of the original right-hand side variables.

4.4 Sample selection and descriptive statistics

I start with all firms for which financial data and S&P's issuer ratings are available from both Compustat and Capital IQ for the 2005-2012 period, respectively. To calculate control variables, I obtain institutional ownership data from Thomson Reuters, analyst data from I/B/E/S, corporate governance data from RiskMetrics, and performance pricing data from Dealscan.

[INSERT TABLE 1]

Table 1 presents descriptive statistics for rated and non-rated firms separately. The table includes only the observations for which there are data available to calculate abnormal accruals and all independent variables. The final sample includes 6116 firm-year observations, 53% of which belong to *RATED* firms.[58] Descriptive statistics from

[57] Free cash flow is calculated as the difference between earnings and total accruals less the average capital expenditures for the last 3 years, divided by average current assets (Dechow, Sloan, & Sweeney, 1996).
[58] The availability of data biases the sample towards larger (and hence, rated) firms. The sample that is based on Compustat-only independent variables is much larger (14450 observations), and only 33% of this sample is *RATED* firms.

Table 1 suggest that the changes in abnormal accruals (*ABACC*) from the pre-FC to the post-FC period are not statistically significant regardless of whether the firm is rated or non-rated. However, while *ABACC* was not different between rated and non-rated firms in the pre-FC period, rated firms had significantly higher abnormal accruals than non-rated firms in the post-FC period. This result provides some support for H1a.

From the main independent variables, only the percentage of firms placed under negative credit watch (*CWNEG*) significantly decreased from the pre-FC to the post-FC period. No significant changes are observed for the percentage of firms with investment grade threshold ratings (*IGT*), minus-notch ratings (*MNOTCH*), or rating triggers (*RTR*). The average issuer rating also decreased by almost half a notch from 12.8 in the pre-FC period to 12.4 in the post-FC period, which is a statistically and economically significant decline.[59] A comparison of firm characteristics between rated and non-rated firms reveals that these firms are different in both the pre-FC and the post-FC periods, highlighting the importance of controlling for these factors in multivariate tests. Specifically, rated firms are larger, more profitable, have better credit quality, and less volatile cash flows. They also have lower working capital, growth, and market-to-book ratio.

4.5 Results from multivariate tests

Table 2 presents the results for H1a using *ABACC* as the dependent variable. In all tests, control variables are winsorized at 1% extremes. Standard errors are obtained via bootstrapping. The first column regression includes only the firm fundamentals as controls (i.e., the variables calculated using only Compustat data), while the second

[59] The issuer ratings corresponding to 12 and 13 are S&P's BBB- & BBB ratings, respectively.

column regression includes all control variables.[60] Results from both columns indicate that, after controlling for various firm characteristics, there was no statistically significant difference in abnormal accruals between rated and non-rated firms in the pre-FC period. Consistent with H1a, abnormal accruals increased significantly in rated firms from the pre-FC to the post-FC period but remained statistically similar in non-rated firms.

[INSERT TABLE 2]

Inferences are similar when *OPINCADJ* is used as the dependent variable instead of *ABACC*. Column 1 of Table 3 presents the results from this test. As in Table 2, control variables are winsorized at 1% extremes and standard errors are obtained via bootstrapping. The regressions include industry fixed effects. Since I use non-rated firms as a benchmark in empirical tests, I calculate the hypothetical adjustments to a firm's operating income in the case of non-rated firms. Such a comparison helps to rule out the possibility that the changes documented for rated firms (if any) from the pre-FC to the post-FC period are due to a general trend in the financial numbers used in the adjustment process. Control variables include the firm characteristics and credit quality proxies defined earlier, plus *OPINC*. *OPINC* is calculated as cash flows from operating activities divided by total assets. I expect firms with good operating performance to have less need to engage in rating adjustments-motivated EM to obtain a positive financial risk assessment from CRAs.

Consistent with rated firms managing the financial numbers that feed into operating income adjustments, results from the first column of Table 3 suggest that *OPINCADJ* is not only significantly higher in rated firms than in non-rated firms in all periods, but also

[60] The aim of the column 1 regression is for the test sample to better reflect the proportion of rated firms to non-rated firms while also controlling for main firm characteristics.

statistically insignificant in non-rated firms (intercept) after controlling for various firm characteristics and industry fixed effects. In addition, consistent with the results documented in Kraft (2015a), *OPINCADJ* is significantly higher in firms with rating triggers than in other rated firms and non-rated firms in the pre-FC period (*RTR* significant at 5%). Since Kraft (2015a) uses proprietary adjustment data obtained from Moody's, confirming her findings using publicly available data increases confidence in the validity of *OPINCADJ*. Importantly for the purposes of this study, and consistent with H1a, results indicate *OPINCADJ* increased significantly in rated firms, but not in non-rated firms, from the pre-FC to the post-FC period.

[INSERT TABLE 3]

Table 4 presents the results for H1b using *ABACC* as the dependent variable. As the statistical significance of control variables is similar to those in Table 2, only the variables of interest are presented in this table. For ease of reference, the z-statistics for the sum of *RATED* and *RTR* (*CWNEG*) and for the changes in these subsamples from the pre-FC to the FC and the post-FC periods are presented below the regression output in Panel A (Panel B).

[INSERT TABLE 4]

Results suggest that the increase in the abnormal accruals of rated firms in the post-FC period was mainly driven by firms with rating triggers. Specifically, when *RTR* and its interactions with *FC* and *PostFC* are included in the main regression (Panel A), the coefficient on *RATED*∗*PostFC* loses its significance. When the regression includes only the Compustat-based control variables (column 1), the increase in abnormal accruals in *RTR* firms is significantly different from that in non-rated firms but not from the increase in other rated firms (*RTR*∗*PostFC* is statistically insignificant but the sum of the

coefficients on *RATED∗PostFC* and *RTR∗PostFC* is significant at 1% with a z-stat of 3.02). When all variables are controlled for (column 2), this increase in *RTR* firms becomes significantly different from other rated firms as well. Results from tests where *OPINCADJ* is the dependent variable (Table 3 column 2), on the other hand, indicate that the magnitude of the increase in *OPINCADJ* is not statistically different between firms with rating triggers and other rated firms (*RTR∗PostFC* statistically insignificant).

CWNEG firms behave somewhat differently from *RTR* firms. When *CWNEG* and its interactions with *FC* and *PostFC* are included in the *ABACC* regressions (Table 4 Panel B), *RATED∗PostFC* retains its significance.[61] The coefficient on *CWNEG∗PostFC*, however, is statistically insignificant despite being positive. Although the coefficient on *CWNEG∗FC* is significant, the sum of the coefficients on *RATED∗FC* and *CWNEG∗FC* equals the sum of the coefficients on *RATED∗PostFC* and *CWNEG∗PostFC*. Therefore, unlike other rated firms, *CWNEG* firms might have started engaging in more accrual-based EM from as early as the FC period. In sum, results from Tables 2-4 suggest that firms with stronger rating-related incentives are likely to engage in more accrual-based EM in response to an increase in rating quality.

Table 5 presents the results for H2a and H2b using *ABACC* as the dependent variable. Consistent with prior literature, firms with issuer ratings at the investment grade threshold engaged in more accrual-based EM than non-rated and other rated firms before the crisis (*IGT* significant at 10% column 1). Results from column 1 indicate that the decrease in the abnormal accruals of *IGT* firms from the pre-FC to the post-FC period was significantly different from the change in the abnormal accruals of other rated firms (*IGT∗PostFC* significantly negative at 5%). However, inconsistent with H2a, this

[61] I do not test whether firms placed under credit watch manage *OPINCADJ* to a greater extent after the crisis as it is unlikely to be feasible within the usual credit watch period, which is 4-5 months on average.

decrease was not statistically different from the decrease in the abnormal accruals of non-rated firms (sum of *RATED∗PostFC* and *IGT∗PostFC* statistically insignificant with a z-stat of 0.12). Tests using *MNOTCH* instead of *IGT* yield similar results (column 2).

[INSERT TABLE 5]

In supplementary analyses, I limit the *IGT* sample to only the firms with the S&P's (Moody's) BBB- (Baa3) rating and rerun the *ABACC* regressions. Since a downgrade from a BBB- (Baa3) rating results in the loss of investment grade status, firms with a BBB- (Baa3) rating are likely to have even stronger incentives to avoid the potentially negative impact of higher rating quality. Inferences from the tests using this alternative definition of *IGT* (untabulated) are similar to those using the original *IGT* specification. Inferences also remain unchanged (and in some cases, are stronger) if I deduct the change in accounts receivable from the change in sales before estimating equation 5 as per Kothari et al. (2005), or if I use other common accrual models to estimate abnormal accruals (untabulated). Narrowing the pre-FC and the post-FC period windows from three to two years or redefining the FC period as in deHaan (2017) provides similar results. Collectively, results from these tests suggest that unlike other rated firms, firms facing strong CRA monitoring do not increase accrual-based EM in response to an increase in rating quality if we measure accrual-based EM using common discretionary accruals proxies.

When I use *OPINCADJ* as the dependent variable in related tests, however, inferences change slightly. Results from Table 6 suggest that the increase in *OPINCADJ* in rated firms is driven by firms that likely face stronger CRA monitoring. Specifically, when *IGT* (or *MNOTCH*) and its interactions with *FC* and *PostFC* are included in the main regression, *RATED∗PostFC* becomes statistically insignificant. The sum of the

coefficients on *RATED∗PostFC* and *IGT∗PostFC* (*MNOTCH∗PostFC*), on the other hand, is significant at 5% (1%) with a z-statistic of 1.98 (2.30). The increase in *OPINCADJ* in firms with minus-notch ratings is higher than that in other rated firms as well.

[INSERT TABLE 6]

In additional analyses, I create a new variable, *OPINCADJALT*, that is similar to *OPINCADJ* but excludes the adjustments due to finance division's income, use of LIFO, and preferred dividends. That is, *OPINCADJALT* excludes items whose manipulation does not (necessarily) imply a change in reporting quality. For example, reducing preferred dividends to increase *OPINCADJ* would imply a change in real activities to influence ratings. Results from *OPINCADJALT* tests (presented in Table 7) are similar to those documented earlier, rendering support to the notion that the findings from Tables 3 and 6 are driven by changes in reporting quality. The only notable differences between the results from the two tests are that *IGT* becomes more significant (at 5% in new tests) and the sum of *RATED∗PostFC* and *IGT∗PostFC* becomes less significant (significant only at 10% in new tests).

[INSERT TABLE 7]

One potential explanation for the differences between the results from *OPINCADJ* and *ABACC* tests is that *OPINCADJ* and *OPINCADJALT* are more precise measures of EM in this study's setting. In particular, they comprise only the financial numbers that are important for the purposes of rating assessment. Managing financial numbers that feed into *OPINCADJ* may be especially attractive for firms facing strong CRA monitoring as the list of adjustments to firms' reported earnings and the financial numbers used in the process is rather lengthy, and even subtle changes to some of these numbers may

accumulate and make a difference for rating assessment. Moreover, not all details related to these financial numbers need to be disclosed to the public. An alternative explanation for the different results is that *OPINCADJ* and *ABACC* may capture different factors or different dimensions of EM, and consequently, respond to different incentives. This issue is not further explored here as it is outside the scope of this thesis.

4.6 Conclusion

In this chapter, I examine how increased rating quality after the FC affected rated firms' reporting quality. I find that abnormal accruals increased in rated firms from the pre-FC to the post-FC period but remained similar in non-rated firms. Consistent with the CRAs' gatekeeper role and monitoring arguments, this effect was muted in firms with investment grade threshold ratings and minus-notch ratings. After the FC, rated firms also started managing the measure of earnings used by CRAs in the rating process. Results suggest that the increase in abnormal accruals was mainly driven by firms with strong rating-related incentives, while the increase in rating adjustments-motivated EM was driven by firms facing strong CRA monitoring.

Since rating quality is a product of the quality of CRA's rating assessment and the quality of information provided to the CRA, one implication of these findings is that the extent of the improvement in rating quality is likely to be lower than that in rating standards due to a decline in rated firms' reporting quality. Consequently, this chapter contributes to the rating quality literature by providing evidence on how a change in rating standards affects firm behavior, which may, in turn, feed into rating quality.

Appendix A: *Variable definitions*

Variables	Definitions
ABACC	Performance-matched residuals from estimating the total accruals model (equation 5). Total accruals are calculated as income before extraordinary items and discontinued operations minus operating cash flows from continuing operations. Each industry-year group is required to have at least 12 observations. Industries are defined based on the two-digit SIC codes. Performance-matching is done by identifying the firm with the closest ROA within the same industry-year and differencing the abnormal accruals of the two firms.
ANAFOL	The number of equity analysts following the firm.
CFTCAPEX	Ratio of net cash flows from operating activities to capital expenditures.
CFTLIAB	Ratio of operating income before depreciation and amortization to total liabilities.
CFVOL	Standard deviation of the firm's cash flows for the last ten years. Cash flows are calculated as operating income before depreciation and amortization minus interest, taxes, and dividends, divided by assets.
CHAIR	Indicator if the CEO is also the chair of the board.
CWNEG	Indicator for firms placed under negative credit watch at least once during the fiscal year.
EXTFIN	Indicator if the firm's free cash flow is less than -0.5. Free cash flow is calculated as the difference between earnings and total accruals less the average capital expenditures for the last three years, divided by average current assets.
FC	Indicator for the financial crisis period (years 2008 and 2009).
GROWTH	Percentage change in sales from year t-2 to year t-1.
IGT	Indicator for firms that have an S&P's (Moody's) issuer rating of BBB- (Baa3) or BB+ (Ba1). If the firm is rated by both agencies, S&P's issuer rating is used.
INDPERC	Percentage of independent directors on the board.
INST	Percentage of institutional holders.

Appendix A *(continued)*: *Variable definitions*

LEV	Sum of short-term and long-term debt, divided by total assets.
MNOTCH	Indicator for firms that have an issuer rating of AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, or B3) from S&P (Moody's).
MTB	Market-to-book ratio, calculated as the book value of assets, less the book value of equity, plus the market value of equity, divided by assets (measured in t-1).
NEGNI	Indicator for firms that had negative earnings for the last two or more years.
OPINC	Cash flows from operating activities divided by total assets.
OPINCADJ	S&P's adjustment to operating income divided by sales. The adjustment measure is calculated as deferred income taxes, minus income taxes, minus capitalized software costs, minus capitalized interest, minus finance division's income (finance division's revenue minus finance division's operating expense), minus 50% of preferred dividends, minus write-downs after tax for the retail industry, plus adjustment due to operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment, minus the decrease in LIFO reserves.
OPINCADJALT	Alternative definition of *OPINCADJ*; its calculation is similar to *OPINCADJ* but excludes the adjustments due to finance division's income, use of LIFO, and preferred dividends.
PostFC	Indicator for the post-crisis period (years 2010 through 2012).
RATED	Indicator for firms that had an issuer rating in both the pre-FC and the post-FC periods.
RATING	Issuer rating from S&P (or Moody's when the firm is not rated by S&P). The variable equals zero if the firm does not have an issuer rating from either rating agency.
ROE	Net income divided by equity.
RTR	Indicator for firms that have at least one debt contract with rating-based performance pricing provisions at the end of the fiscal year.
SIZE	Natural log of total assets.
WCAP	Working capital divided by total assets.

ZSCORE	Altman's Z-score (measured at t-1), calculated as $3.3 * \text{EBIT} / \text{TA} + \text{Sales} / \text{TA} + 1.4 * \text{Retained Earnings} / \text{TA} + 1.2 * \text{WCAP} / \text{TA} + 0.6 * \text{Market value of equity} / \text{Total Liab}$, where TA is total assets.

Appendix B: *Numerical values corresponding to S&P's and Moody's ratings*

Group	Numeric value	S&P rating	Moody's rating
Investment grade	21	AAA	Aaa
	20	AA+	Aa1
	19	AA	Aa2
	18	AA-	Aa3
	17	A+	A1
	16	A	A2
	15	A-	A3
	14	BBB+	Baa1
	13	BBB	Baa2
	12	BBB-	Baa3
Speculative grade	11	BB+	Ba1
	10	BB	Ba2
	9	BB-	Ba3
	8	B+	B1
	7	B	B2
	6	B-	B3
	5	CCC+	Caa1
	4	CCC	Caa2
	3	CCC-	Caa3
	2	CC, C	Ca
In default	1	D	C
Not rated	0		

Table 1: *Descriptive statistics*

	Rated firms					Non-rated firms				
	Pre-FC		Post-FC		Change	Pre-FC		Post-FC		Change
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
ABACC	-0.009	0.080	-0.005	0.073	0.005	-0.006	0.093	-0.011^{-}	0.094	-0.005
ANAFOL	14.707	9.645	16.270	9.614	1.563^{a}	10.770^{-}	8.073	11.472^{-}	8.904	0.702
CFTCAPEX	3.049	3.432	3.747	4.721	0.698^{a}	4.048^{+}	6.290	4.431	14.411	0.383
CFTLIAB	0.292	0.211	0.263	0.175	-0.029^{a}	0.573^{+}	0.678	0.571^{+}	0.739	-0.002
CFVOL	0.037	0.062	0.038	0.053	0.001	0.115^{+}	0.239	0.133^{+}	0.426	0.018
CHAIR	0.706	0.456	0.551	0.498	-0.155^{a}	0.552^{-}	0.498	0.461^{-}	0.499	-0.091^{ab}
CWNEG	0.141	0.348	0.077	0.267	-0.064^{a}	-	-	-	-	-
EXTFIN	0.055	0.228	0.101	0.301	0.046^{a}	0.038	0.192	0.046^{-}	0.209	0.008^{b}
GROWTH	0.107	0.147	0.019	0.200	-0.088^{a}	0.160^{+}	0.179	0.067^{+}	0.238	-0.093^{a}
IGT	0.196	0.397	0.222	0.416	0.026	-	-	-	-	-
INDPERC	0.785	0.122	0.823	0.096	0.038^{a}	0.729^{-}	0.129	0.770^{-}	0.110	0.041^{a}
INST	0.774	0.149	0.765	0.199	-0.009	0.803^{+}	0.161	0.787^{+}	0.190	-0.016^{a}
LEV	0.255	0.140	0.279	0.151	0.024^{a}	0.113^{-}	0.144	0.112^{-}	0.158	-0.001^{b}
MNOTCH	0.300	0.458	0.303	0.460	0.003	-	-	-	-	-
MTB	1.837	0.764	1.568	0.627	-0.269^{a}	2.594^{+}	1.564	2.140^{+}	1.327	-0.454^{ab}
NEGNI	0.025	0.156	0.052	0.222	0.027^{a}	0.049^{+}	0.217	0.068	0.252	0.019
RATING	12.788	2.899	12.396	2.935	-0.392^{a}	-	-	-	-	-
ROE	0.169	0.332	0.122	0.472	-0.047^{a}	0.138^{-}	0.223	0.139	0.282	0.001^{b}

Table 1 *(continued)***:** *Descriptive statistics*

RTR	0.603	0.489	0.575	0.495	-0.028	-	-	-	-	-
SIZE	8.657	1.198	8.846	1.287	0.189[a]	6.501[-]	1.019	6.643[-]	1.077	0.142[a]
WCAP	0.129	0.145	0.152	0.143	0.023[a]	0.315[+]	0.220	0.319[+]	0.207	0.004
ZSCORE	3.565	2.612	3.008	1.829	-0.557[a]	7.825[+]	6.942	6.494[+]	5.871	-1.954

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. Rated firms are firms that had an issuer rating in a given fiscal year. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. The definitions of variables can be found in Appendix A.

Change is calculated as the change in variable mean from the pre-FC period to the post-FC period. [a] superscript indicates whether these changes are statistically significant at 5%. [b] superscript indicates whether the *Change* for the subsample of non-rated firms is significantly different from the *Change* for the subsample of rated firms. When [+] ([-]) superscript appears under "Mean" column, it indicates whether the variable mean for the subsample of non-rated firms in a given period (i.e. pre-FC or post-FC) is significantly greater (smaller) at 5% than the variable mean for the subsample of rated firms in that same period.

Table 2: *Post-FC accrual-based EM in rated firms*

Dependent variable:	ABACC	
RATED	-0.007	-0.003
	(-0.93)	(-0.32)
PostFC	-0.001	-0.002
	(-0.25)	(-0.55)
RATED ∗ PostFC	0.010**	0.013**
	(2.32)	(2.29)
FC	0.003	-0.001
	(1.00)	(-0.34)
RATED ∗ FC	0.004	0.006
	(0.82)	(0.83)
LEV	0.016**	0.008
	(2.09)	(0.85)
SIZE	-0.006***	0.003**
	(-6.86)	(2.50)
GROWTH	0.001	-0.003
	(0.30)	(-0.31)
MTB	-0.005***	-0.002
	(-2.87)	(-0.91)
RATING	0.001	-0.001
	(1.53)	(-0.95)
ZSCORE	-0.000	-0.001**
	(-1.13)	(-2.32)
CFVOL	-0.003	-0.016***
	(-1.59)	(-3.04)
WCAP	0.033***	0.033***
	(3.08)	(2.98)
CFTLIAB	-0.014***	-0.002
	(-5.75)	(-0.26)
CFTCAPEX	-0.001***	-0.001***
	(-6.14)	(-4.92)
ROE	0.007**	0.013***
	(2.54)	(4.17)
EXTFIN	-0.061***	-0.035***
	(-11.65)	(-5.42)
NEGNI	-0.003	0.003
	(-0.83)	(0.43)
ANAFOL		-0.001***
		(-5.79)
INST		-0.007
		(-1.18)

Table 2 *(continued)*: *Post-FC accrual-based EM in rated firms*

CHAIR		0.001
		(0.54)
INDPERC		-0.001
		(-0.10)
Observations	14450	6116
Adjusted R^2	0.049	0.046

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.
FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. The dependent variable, *ABACC*, refers to abnormal accruals. The definitions of all other variables can be found in Appendix A.

Table 3: *Rating adjustments-motivated EM in rated firms and firms with rating triggers*

Dependent variable:	OPINCADJ	
RATED	0.020***	0.020***
	(5.32)	(6.32)
RTR		0.004**
		(2.15)
PostFC	0.001	0.000
	(0.33)	(0.23)
RATED ∗ PostFC	0.004*	0.005**
	(1.85)	(2.01)
RTR ∗ PostFC		-0.002
		(-0.96)
FC	0.001	0.001
	(0.27)	(0.23)
RATED ∗ FC	0.001	0.002
	(0.49)	(0.66)
RTR ∗ FC		-0.002
		(-0.95)
LEV	0.013**	0.013**
	(2.44)	(2.29)
SIZE	-0.002***	-0.002***
	(-4.61)	(-3.82)
MTB	-0.004***	-0.004***
	(-4.37)	(-4.78)
OPINC	-0.092***	-0.091***
	(-6.04)	(-6.11)
RATING	-0.002***	-0.002***
	(-8.55)	(-9.99)
WCAP	0.024***	0.024***
	(4.04)	(3.27)
CFVOL	-0.001	-0.001
	(-0.48)	(-0.56)
ZSCORE	-0.001*	-0.001*
	(-1.84)	(-1.72)
CFTLIAB	-0.027***	-0.027***
	(-7.88)	(-8.26)
CFTCAPEX	-0.000***	-0.000**
	(-2.82)	(-2.38)

Industry FE	Yes	Yes
Observations	12003	11840
Adjusted R^2	0.357	0.357
z-stat for (RATED + RTR)		6.42
z-stat for FC∗(RATED + RTR)		0.10
z-stat for PostFC∗(RATED + RTR)		1.15

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RTR* equals one if the firm had at least one private debt contract that included a rating trigger at the end of the fiscal year, and zero otherwise. In column 2, the sample size is smaller because I exclude firm-year observations when the firm has a debt contract that includes a rating trigger but does not have an issuer rating.

OPINCADJ is calculated as operating income before depreciation and amortization minus income taxes, plus deferred income taxes, minus capitalized software costs, minus capitalized interest, minus finance division's income (finance division's revenue minus finance division's operating expense), minus 50% of preferred dividends, minus write-downs after tax for the retail industry, plus depreciation portion of operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment, minus the decrease in LIFO reserves from the previous year. The definitions of all other variables can be found in Appendix A.

Since *RTR* is a subset of *RATED*, its interaction with *RATED* does not appear in the regression. For ease of reference, the z-statistics for the sum of *RATED* and *RTR* and for the changes in *RTR* subsample from the pre-FC to the FC and post-FC periods are presented below the regression output in column 2.

Table 4 – *Panel A*: *Post-FC accrual-based EM in firms with rating triggers*

Dependent variable:	ABACC	
RATED	-0.004	0.001
	(-0.59)	(0.12)
RTR	0.000	-0.002
	(0.02)	(-0.46)
PostFC	-0.001	-0.003
	(-0.38)	(-1.06)
RATED ∗ PostFC	0.007	0.009
	(1.16)	(1.42)
RTR ∗ PostFC	0.008	0.012*
	(1.52)	(1.84)
FC	0.003	-0.003
	(0.88)	(-0.70)
RATED ∗ FC	0.002	0.002
	(0.37)	(0.30)
RTR ∗ FC	0.005	0.009
	(0.87)	(1.24)
Control variables	Compustat only	All
Observations	14342	5983
Adjusted R^2	0.049	0.047
z-stat for (RATED + RTR)	-0.56	-0.13
z-stat for FC∗(RATED + RTR)	1.33	1.45
z-stat for PostFC∗(RATED + RTR)	3.02	3.30

Table 4 – *Panel B*: *Post-FC accrual-based EM in firms placed under negative credit watch*

Dependent variable:	ABACC	
RATED	-0.008	-0.002
	(-1.03)	(-0.30)
CWNEG	-0.005	-0.004
	(-0.86)	(-0.47)
PostFC	-0.001	-0.002
	(-0.21)	(-0.48)
RATED ∗ PostFC	0.009**	0.012**
	(2.04)	(2.06)
CWNEG ∗ PostFC	0.012	0.009
	(1.29)	(0.76)
FC	0.003	-0.001
	(0.99)	(-0.32)
RATED ∗ FC	0.001	0.005
	(0.13)	(0.73)
CWNEG ∗ FC	0.021*	0.005
	(1.90)	(0.43)
Control variables	Compustat only	All
Observations	14500	6116
Adjusted R^2	0.049	0.046
z-stat for (RATED + CWNEG)	-1.40	-0.54
z-stat for FC∗(RATED + CWNEG)	2.03	0.85
z-stat for PostFC∗(RATED + CWNEG)	2.13	1.68

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RTR* equals one if the firm had at least one private debt contract that included a rating trigger at the end of the fiscal year, and zero otherwise. In Panel A, the sample size is smaller than that in Table 2 because I exclude firm-year observations when the firm has a debt contract that includes a rating trigger but does not have an issuer rating. *CWNEG* equals one if the firm was placed under negative credit watch during the fiscal year, and zero otherwise. The dependent variable, *ABACC*, refers to abnormal accruals. Control variables are the same as in Table 2. The definitions of all variables can be found in Appendix A.

Since *RTR* and *CWNEG* are subsets of *RATED*, their interactions with *RATED* do not appear in the regressions. For ease of reference, the z-statistics for the sum of *RATED* and *RTR* (*CWNEG*) and for the changes in these subsamples from the pre-FC to the FC and post-FC periods are presented below the regression output in Panel A (Panel B).

Table 5: *Post-FC accrual-based EM in firms with investment grade threshold ratings and minus-notch ratings*

Dependent variable:	ABACC	
	HIMON = IGT	*HIMON = MNOTCH*
RATED	-0.006	-0.005
	(-0.73)	(-0.45)
HIMON	0.011*	0.008
	(1.84)	(1.58)
PostFC	-0.002	-0.002
	(-0.53)	(-0.67)
RATED ∗ PostFC	0.017***	0.018***
	(2.77)	(3.04)
HIMON ∗ PostFC	-0.016**	-0.017***
	(-2.03)	(-2.81)
FC	-0.001	-0.001
	(-0.37)	(-0.30)
RATED ∗ FC	0.007	0.008
	(1.11)	(0.98)
HIMON ∗ FC	-0.008	-0.006
	(-0.85)	(-0.84)
Control variables	All	All
Observations	6116	6116
Adjusted R^2	0.046	0.046
z-stat for (RATED + HIMON)	0.53	0.32
z-stat for FC∗(RATED + HIMON)	-0.06	0.16
z-stat for PostFC∗(RATED + HIMON)	0.12	0.18

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *HIMON* is not a variable by itself, and stands for *IGT* in column 1 and *MNOTCH* in column 2. *IGT* equals one if the firm has BBB-/BB+ rating from S&P or Baa3/Ba1 rating from Moody's, and zero otherwise. *MNOTCH* equals one if a firm has one of the following issuer ratings from S&P (Moody's): AA-, A-, BBB-, BB-, B- (Aa3, A3, Baa3, Ba3, B3). The dependent variable, *ABACC*, refers to abnormal accruals. Control variables are the same as in Table 2. The definitions of all variables can be found in Appendix A.

Since *IGT* and *MNOTCH* are subsets of *RATED*, their interactions with *RATED* do not appear in the regressions. For ease of reference, the z-statistics for the sum of *RATED* and *IGT* (*MNOTCH*) and for the changes in these subsamples from the pre-FC to the FC and post-FC periods are presented below the regression output in column 1 (column 2).

Table 6: *Rating adjustments-motivated EM in firms with investment grade threshold ratings and minus-notch ratings*

Dependent variable:	OPINCADJ	
	HIMON = IGT	*HIMON = MNOTCH*
RATED	0.019***	0.021***
	(5.77)	(6.14)
HIMON	0.004*	-0.001
	(1.82)	(-0.68)
PostFC	0.001	0.001
	(0.24)	(0.24)
RATED ∗ PostFC	0.003	0.002
	(1.20)	(0.77)
HIMON ∗ PostFC	0.002	0.004*
	(0.87)	(1.83)
FC	0.001	0.001
	(0.23)	(0.25)
RATED ∗ FC	0.002	0.001
	(0.62)	(0.42)
HIMON ∗ FC	-0.002	0.000
	(-0.69)	(0.04)
Industry FE	Yes	Yes
Control variables	Yes	Yes
Observations	12003	12003
Adjusted R^2	0.357	0.357
z-stat for (RATED + HIMON)	6.33	5.46
z-stat for FC∗(RATED + HIMON)	-0.26	0.41
z-stat for PostFC∗(RATED + HIMON)	1.98	2.30

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *HIMON* is not a variable by itself, and stands for *IGT* in column 1 and *MNOTCH* in column 2. *IGT* equals one if the firm has BBB-/BB+ rating from S&P or Baa3/Ba1 rating from Moody's, and zero otherwise. *MNOTCH* equals one if a firm has one of the following issuer ratings from S&P (Moody's): AA-, A-, BBB-, BB-, B- (Aa3, A3, Baa3, Ba3, B3).

OPINCADJ is calculated as operating income before depreciation and amortization minus income taxes, plus deferred income taxes, minus capitalized software costs, minus capitalized interest, minus finance division's income (finance division's revenue minus finance division's operating expense), minus 50%

of preferred dividends, minus write-downs after tax for the retail industry, plus depreciation portion of operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment, minus the decrease in LIFO reserves from the previous year. Control variables are the same as in Table 3. The definitions of all variables can be found in Appendix A.

Since *IGT* and *MNOTCH* are subsets of *RATED*, their interactions with *RATED* do not appear in the regressions. For ease of reference, the z-statistics for the sum of *RATED* and *IGT* (*MNOTCH*) and for the changes in these subsamples from the pre-FC to the FC and post-FC periods are presented below the regression output in column 1 (column 2).

Table 7: *Rating adjustments-motivated EM in rated firms – alternative definition of OPINCADJ*

Dependent variable	OPINCADJALT			
		RAINC = RTR	*RAINC = IGT*	*RAINC = MNOTCH*
RATED	0.020***	0.020***	0.019***	0.020***
	(5.60)	(5.28)	(5.03)	(6.56)
RAINC		0.003*	0.005**	-0.001
		(1.80)	(2.22)	(-0.55)
PostFC	0.001	0.001	0.001	0.001
	(0.65)	(0.64)	(0.67)	(0.71)
RATED ∗ PostFC	0.004*	0.004*	0.003	0.002
	(1.70)	(1.69)	(1.43)	(1.03)
RAINC ∗ PostFC		-0.001	0.001	0.004*
		(-0.55)	(0.44)	(1.73)
FC	0.000	0.000	0.000	0.000
	(0.04)	(0.02)	(0.04)	(0.03)
RATED ∗ FC	0.002	0.004	0.003	0.002
	(1.17)	(1.29)	(1.23)	(0.96)
RAINC ∗ FC		-0.002	-0.003	0.000
		(-0.76)	(-0.96)	(0.05)
Observations	12003	11840	12003	12003
Adjusted R^2	0.398	0.398	0.398	0.398
z-stat for (RATED + RTR)		5.81	6.39	6.41
z-stat for FC∗(RATED + RTR)		0.47	-0.07	0.80
z-stat for PostFC∗(RATED + RTR)		1.23	1.67	2.27

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics provided in brackets. *FC* period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RAINC* is not a variable by itself, and stands for *RTR* in column 2, *IGT* in column 3, and *MNOTCH* in column 4. *IGT* equals one if the firm has BBB-/BB+ rating from S&P or Baa3/Ba1 rating from Moody's, and zero otherwise. *MNOTCH* equals one if a firm has one of the following issuer ratings from S&P (Moody's): AA-, A-, BBB-, BB-, B- (Aa3, A3, Baa3, Ba3, B3). *RTR* equals one if the firm had at least one private debt contract that included a rating trigger at the end of the fiscal year, and zero otherwise. In column 2, the sample size is smaller because I exclude firm-year observations when the firm has a debt contract that includes a rating trigger but does not have an issuer rating.

OPINCADJALT is calculated as operating income before depreciation and amortization minus income taxes, plus deferred income taxes, minus capitalized software costs, minus capitalized interest, minus write-downs after tax for the retail industry, plus depreciation portion of operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment. Control variables are the same as in Table 3. The definitions of all variables can be found in Appendix A.

Since *RTR*, *IGT* and *MNOTCH* are subsets of *RATED*, their interactions with *RATED* do not appear in the regressions. For ease of reference, the z-statistics for the sum of *RATED* and each of the three variables, and for the changes in these subsamples from the pre-FC to the FC and post-FC periods are presented below the regression output.

Chapter 5

Rating quality and real firm decisions

Abstract

This chapter examines changes in rated firms' real activities management and liquidity in response to an increase in rating quality. Results suggest that there was no change in real EM, but a reduction in rated firms' financial risk in the post-FC period. Specifically, I find that rated firms increased their liquidity to a greater extent after the FC than non-rated firms, and the extent of the increase was stronger in firms with higher rating-related incentives. These findings expand our understanding of how rated firms respond to a change in rating quality by showing its impact on real firm decisions. The results documented in this chapter are consistent with the earlier findings that when CRAs tighten their rating standards, firms are likely to take actions that would earn them a more positive rating assessment.

5.1 Introduction

Having documented that an increase in rating quality leads to a decline in rated firms' reporting quality, in this chapter I continue exploring other facets of firms' responses to an increase in rating quality with an emphasis on real firm decisions. The chapter focuses on two potential changes in rated firms' behavior. First, it investigates whether tighter rating standards prompted firms to engage more in real activities management since it is unclear if the increase in accrual-based EM as documented in the previous chapter was adequate to influence firms' ratings. Second, motivated by CRAs' rating criteria, it explores the possibility that the increase in rating quality not only incentivized firms to influence the CRAs' perception of their credit risk but also encouraged firms to reduce their financial risk.

There is ample empirical and survey evidence from prior literature indicating that firms engage in real activities management to meet or beat certain earnings benchmarks.[62] Non-aggressive real EM can be successfully utilized by firms to achieve their desired rating to a degree that is difficult for CRAs to detect. However, in the context of this study's setting, it may be a risky strategy for influencing the firm's ratings because real activities management can negatively affect the firm's future cash flows (Bhojraj, Hribar, Picconi, & McInnis, 2009; Cohen & Zarowin, 2010). Since CRAs closely monitor how the firm's net cash inflow is expected to change in the near future, real activities management can earn the firm a negative rating assessment if rating agencies consider the changes to operating activities detrimental to future profitability. Unlike almost any other outsiders, rating agencies can access firm-specific information on demand, and if necessary, hold private meetings with firms' managers to clarify issues. Therefore, firms

[62] For example, see Graham, Harvey, and Rajgopal (2005), Baber, Fairfield, and Haggard (1991), Bushee (1998), Roychowdhury (2006), Cohen and Zarowin (2010), and Zang (2012).

need to weigh the benefits of avoiding a potential downgrade against the risk of a negative rating assessment and/or the loss of long-term firm value (which itself can result in a downgrade in the future).

To test whether rated firms increased real activities management in the post-FC period, I compare changes in abnormal CFO, abnormal production costs, abnormal discretionary expenses, and abnormal SG&A expenses in rated firms (and firms with rating-related incentives) to that in non-rated firms (Gunny, 2010; Roychowdhury, 2006). Consistent with the argument that managing real activities for rating purposes is riskier, results indicate that the change in real EM in rated firms or firms with stronger rating-related incentives from the pre-FC to the post-FC period was not statistically different from that of non-rated firms. Tests performed on the subsample of firms with investment grade threshold ratings and minus-notch ratings provide similar inferences.

I focus on liquidity as a means of reducing financial risk for two reasons. First, liquidity is considered an important determinant of financial risk by rating agencies (e.g., see S&P (2013b)). Liquidity analysis not only constitutes a separate analysis during the rating process, but it also has become an increasingly important part of rating assessment since the FC (S&P, 2008c). Second, increasing accessible cash surplus helps improve the firm's debt ratios for the purposes of rating assessment. Specifically, cash surplus is netted against debt as the last adjustment to the debt figure (S&P, 2013b). The rationale behind this adjustment is that a company with higher levels of accessible cash surplus can more readily pay off its immediate obligations when it goes through difficult times. An implication of this discussion is that firms can improve their ratings by increasing their liquidity, provided that doing so does not negatively affect future profitability.

I use the excess cash measure from Opler et al. (1999) instead of total cash holdings as a proxy for liquidity because only cash that is immediately available to pay off the firm's obligations is netted against debt during the rating process. Results indicate that while rated firms held significantly less excess cash both before and after the FC than non-rated firms, after the FC they increased their excess cash holdings more than non-rated firms. There is also evidence to suggest that in the post-FC period, firms increase their excess cash to a greater extent (or decrease their excess cash to a lesser extent) when placed under negative credit watch. Although credit watches are usually initiated and resolved before the fiscal year-end, CRA analysts and firm managers continually communicate for the duration of the credit watch, and managers can commit to, or signal their intention to, improve liquidity to avoid a downgrade once the credit watch resolves. Taken together, results from the liquidity tests suggest that the improvements in rating standards may lead rated firms to reduce their financial risk.

This chapter expands our knowledge on firms' potential responses to a change in rating quality. First, it provides evidence suggesting that firms are unlikely to engage in real EM in response to an increase in rating quality, possibly because of its potentially negative impact on their future cash flows. Second, to the best of my knowledge, it is the first study to document a change in firms' liquidity that is driven by rating-related incentives.

The rest of the chapter is structured as follows. Section 5.2 discusses the related literature and develops predictions. Section 5.3 provides an outline of the research design. Section 5.4 discusses the sample selection procedure and descriptive statistics. Section 5.5 discusses results from multivariate tests. Section 5.6 concludes.

5.2 Predictions

5.2.1 Rating quality and real activities management

The extent to which firms engage in real activities management in response to an increase in rating quality is likely to depend on the costs and benefits of real EM when used to influence ratings. The major advantage of real EM is that it is difficult to distinguish from real company decisions, and therefore, harder to detect. However, managing real activities is also costly because it may negatively affect the firm's future cash flows. Although there is some evidence suggesting that firms engaging in operating activities management to just meet or beat earnings benchmarks are likely to have relatively better ROA and stock price in the subsequent year (Gunny, 2010), findings from most studies render support to the presumption that real EM has a negative impact on long-term profitability and stock performance.[63]

Given that a firm's ability to pay off its obligations significantly depends on its future cash flows, CRAs pay additional attention to how the firm's net cash inflow is expected to change within the next few years. Real EM may thus lead to a negative rating assessment from CRAs if rating agencies consider the changes to operating activities detrimental to future profitability. Consequently, the extent to which a firm will engage in real EM in response to an increase in rating quality is likely to depend on whether the benefits of avoiding a potential downgrade (or the potential costs of a downgrade) are significant enough to warrant the potential loss of long-term firm value or the more immediate risk of a negative rating assessment. Such incentives are likely to be strongest in firms with minus-notch ratings, lowest investment grade ratings, and debt contracts

[63] See Baber et al. (1991), Bens, Nagar, and Wong (2002), Bhojraj et al. (2009), and Cohen and Zarowin (2010).

that include a rating trigger because a rating downgrade has bigger consequences for these firms (discussed in earlier chapters).

Another factor that may influence the firms' willingness to increase real EM in response to an increase in rating quality is the cost and flexibility of misreporting. Prior research finds that the extent of the firm's engagement in real EM is positively associated with the costs of meeting or beating earnings benchmarks using accrual-based EM (Cohen, Dey, & Lys, 2008; Cohen & Zarowin, 2010; Zang, 2012). Therefore, if the increase in other forms of EM after the FC (as documented in Chapter 4) was sufficient to obtain the firms' desired ratings, no change in real activities management might have occurred even in firms with strong rating-related incentives.

5.2.2 Rating quality and liquidity

I also explore the possibility that, instead of managing earnings to prevent potential downgrades, firms took steps to decrease their financial risk in response to increased rating quality. I focus on increasing cash and short-term investments – the most important source of liquidity – as a means of decreasing financial risk for two reasons, both motivated by S&P's rating criteria. First, after the FC, liquidity analysis has become an increasingly important part of the rating process (S&P, 2008c). Unlike most other rating factors that are blended together in assessing a firm's risk profile, liquidity is assessed "as an independent characteristic of the specific company" because "a lack of liquidity could precipitate the default of an otherwise healthy entity" (S&P, 2010). Second, cash and liquid investments play an important role during the ratio analysis stage of the rating process. Specifically, cash surplus is netted against debt as the last adjustment to the debt

figure that CRAs use in financial ratios.[64] The rationale behind this adjustment is that a company with higher levels of accessible cash surplus can more readily pay off its immediate obligations when it goes through difficult times. Whether the accumulation of cash to prevent a potential downgrade occurs at the expense of foregone profitable investment opportunities or is value-enhancing is beyond the scope of the research question addressed in this thesis.

5.3 Research design

5.3.1 Empirical strategy and main variables

The empirical strategy used in this chapter is similar to that used in Chapter 4. Specifically, I test whether the changes in firms' real activities management and liquidity from the pre-FC to the post-FC period are different in rated firms, firms with strong rating-related incentives, and firms facing strong CRA monitoring. Proxies for real activities management comprise Roychowdhury (2006) real EM measures and Gunny (2010) measure of abnormal selling, general, and administrative (SG&A) expenses. The control variables in real EM tests are the same as those used in accrual-based EM tests in Chapter 4 (see Appendix A or Appendix I for variable definitions). I use the measure of excess cash from Opler et al. (1999) as a proxy for liquidity. Using excess cash instead of total cash holdings as the dependent variable is more appropriate for the purposes of this study because only cash that is immediately available (surplus cash) to pay off short-term obligations is netted against debt during rating assessment.

The main independent variables are as defined in Chapter 4, but I briefly describe them here as well for convenience. The financial crisis (*FC*) period spans from January

[64] For more information on this process, see S&P (2013b).

2008 to December 2009. The pre-crisis (*PreFC*) and the post-crisis (*PostFC*) periods cover the three years before and after the *FC* period, respectively. *RATED* is a binary variable that equals one if a firm had an issuer rating from S&P or Moody's in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RTR* and *CWNEG* indicate the set of firms likely to have strong rating-related incentives.[65] *RTR* refers to firms that, at the end of the fiscal year, had at least one private debt contract that included a rating trigger. *CWNEG* equals one if the firm was placed under negative credit watch at least once during the fiscal year, and zero otherwise. *IGT* and *MNOTCH* denote firms where CRA monitoring is likely to be stronger. *IGT* refers to firms that are at the investment grade threshold and have either the S&P's (Moody's) issuer rating of BBB- (Baa3) or BB+ (Ba1). *MNOTCH* is an indicator for firms that have a minus-notch rating, i.e., an issuer rating of AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, or B3) from S&P (Moody's).

5.3.2 Empirical proxies for real activities management

The real EM proxies are obtained by estimating equations 1 through 4 for each industry-year and performance-matching the residuals from these regressions. Consequently, *ABCFO* refers to performance-matched abnormal cash flows; *ABDEXP* refers to performance-matched abnormal discretionary expenses; *ABPROD* refers to performance-matched abnormal production costs; and *ABSGA* refers to performance-matched abnormal SG&A. The equations used to generate real EM proxies are:

$$CFO_{it}/A_{it-1} = \alpha_0 + \alpha_1(1/A_{it-1}) + \gamma_1(S_{it}/A_{it-1}) + \gamma_2 \Delta S_{it}/A_{it-1} + \theta_t \qquad (1)$$

[65] See subsection 4.3.1 of Chapter 4 for the discussion about why *RTR* and *CWNEG* firms are likely to have strong rating-related incentives.

$$PROD_{it}/A_{it-1} = \alpha_0 + \alpha_1(1/A_{it-1}) + \gamma_1(S_{it}/A_{it-1}) + \gamma_2 \Delta S_{it}/A_{it-1} + \gamma_3 \Delta S_{it-1}/A_{it-1} + \mu_t \quad (2)$$

$$DEXP_{it}/A_{it-1} = \alpha_0 + \alpha_1(1/A_{it-1}) + \gamma_1 S_{it-1}/A_{it-1} + \vartheta_{it} \quad (3)$$

$$SGA_{it}/A_{it-1} = \alpha_0 + \alpha_1(1/A_{it-1}) + \gamma_1 MV_{it} + \gamma_2 Q_{it} + \gamma_3(INT_{it}/A_{it-1}) + \gamma_4(\Delta S_{it}/A_{it-1}) + \gamma_5 (\Delta S_{it}/A_{it-1}) * DD + \partial_{it} \quad (4)$$

where *A* is total assets; Δ*S* is the change in sales from last year; *MV* is the natural log of market value; *Q* is Tobin's Q; *INT* (internal funds) is the sum of income before extraordinary items, research and development costs, and depreciation and amortization. *DD* is an indicator variable equal to one if sales decreased from period t-1 to t. *CFO* is cash flows from operating activities. *SGA* is selling, general and administrative expenses. *PROD* (production costs) is the sum of cost of goods sold and change in inventory. *DEXP* (discretionary expenditures) is the sum of SG&A, research and development costs, and advertising expenses.

Equations 1 through 3 are based on Dechow, Kothari, and Watts (1998) and Roychowdhury (2006), whereas equation 4 is based on Gunny (2010). Abnormally high production costs for a given sales level are indicative of firms' attempt at managing earnings through excessive price discounts or overproduction (Roychowdhury, 2006). Abnormally low discretionary expenses, including SG&A, are indicative of reducing discretionary expenditures to boost earnings. The change in abnormal cash flows can be positive or negative depending on the strength of other real EM techniques as price discounts and overproduction have a negative effect on abnormal CFO, while reducing discretionary expenditures has a positive effect (Roychowdhury, 2006). If firms also managed the classification and timing of cash flows to boost CFO as per Lee (2012), however, firms with strong rating-related incentives likely had a bigger increase in abnormal CFO from the pre-FC to the post-FC period than other firms.

5.3.3 Empirical proxy for liquidity

The empirical proxy for liquidity, excess cash (*EXCASH*), is residuals from Opler et al. (1999) model of corporate cash holdings augmented by additional explanatory variables found to be important in follow-up studies as well as the credit quality indicators defined in Chapter 4:

$$CASH = \beta_0 + \beta_1 MTB + \beta_2 NETWC + \beta_3 SIZE + \beta_4 EARNOP + \beta_5 LEV + \beta_6 CFVOL + \beta_7 CAPEX + \beta_8 ACQ + \beta_9 DIV + \beta_{10} INST + \beta_{11} ZSCORE + \beta_{12} CFTLIAB + \beta_{13} CFTCAPEX + \beta_{14} REVOLVER + \beta_{15} DEBTIS + Industry\ fixed\ effects + Year\ fixed\ effects + \varepsilon \quad (5)$$

where *CASH* is the natural log of the firm's cash holdings. Cash holdings is calculated as the cash and short-term investments divided by assets minus cash and short-term investments. For simplicity, hereafter I refer to cash and short-term investments as cash.

Following Opler et al. (1999), *NETWC* is defined as working capital minus cash, divided by total assets minus cash. *EARNOP* is earnings before depreciation and amortization minus dividends, divided by total assets minus cash. *CAPEX* is capital expenditures divided by total assets. *ACQ* is acquisition expenditures divided by total assets. *DIV* is an indicator variable equal to one if the firm has paid out dividends in a given financial year, and zero otherwise. *REVOLVER* is an indicator variable equal to one if the firm acquired a revolving credit line facility with a maturity of at least 12 months in that fiscal year, and zero otherwise. *DEBTIS* is calculated as issued debt minus retired debt, divided by total assets. The rest of the control variables included in equation 5 are as defined in Chapter 4. Since *EXCASH* comprises residuals obtained from another regression, I correct for the bias stemming from the use of residuals as the dependent variable via the same method described in subsection 4.3.4 (Chen et al., 2018).

5.4 Sample and descriptive statistics

I start with all firms for which financial data and S&P's issuer ratings are available from both Compustat and Capital IQ for the 2005-2012 period, respectively. To calculate control variables, I obtain institutional ownership data from Thomson Reuters, analyst data from I/B/E/S, corporate governance data from RiskMetrics, and performance pricing data from Dealscan.

[INSERT TABLE 1]

Table 1 presents descriptive statistics for rated and non-rated firms separately. For parsimony, only the variables of interest and control variables used in the cash holdings model are included in the table (for other control variables, see Table 1 of Chapter 4). The sample includes 14,917 firm-year observations. Descriptive statistics suggest that there was no significant change in any of the real EM proxies from the pre-FC to the post-FC period in either rated firms or non-rated firms. However, non-rated firms had significantly higher abnormal discretionary expenses (*ABDEXP*) and significantly lower abnormal SG&A expenses (*ABSGA*) than rated firms in both periods. Unlike the real EM variables, excess cash (*EXCASH*) increased in the post-FC period in both subsamples of firms, but the increase was significantly higher in rated firms than in non-rated firms. Inferences from examining the changes in main independent variables from the pre-FC to the post-FC period are similar to those in section 4.4 of Chapter 4.

5.5 Results

Table 2 presents the results from base real EM tests. In all tests, control variables are winsorized at 1% extremes. Standard errors are obtained via bootstrapping. Since the tests including Compustat-only control variables produce results that are similar to those

including all control variables (as in accrual-based EM tests), I present only the latter. Results from Panel A suggest that in both the pre-FC and the post-FC periods, rated firms had, on average, significantly less abnormal cash flows (*ABCFO*), abnormal SG&A expenses (*ABSGA*), and abnormal discretionary expenses (*ABDEXP*), and significantly more abnormal production costs (*ABPROD*) than non-rated firms. Of the four real EM proxies, only *ABPROD* significantly decreased, and *ABDEXP* significantly increased in the post-FC period. Importantly for the purposes of this study, however, these changes were not statistically different between rated and non-rated firms (*RATED∗PostFC* is insignificant in all columns). One interesting result from Panel A is that the sum of the coefficients on *PostFC* and *RATED∗PostFC* is insignificant in column 2, suggesting that abnormal production costs decreased in non-rated firms but remained similar in rated firms. Neither the level of, nor the changes in, real EM proxies in firms with rating triggers (*RTR*) are significantly different from that in other rated firms (Panel B).[66]

[INSERT TABLE 2]

Table 3 presents the results from estimating the main regressions with *IGT* (Panel A) and *MNOTCH* (Panel B) included. *IGT∗PostFC* and *MNOTCH∗PostFC* are positive and significant in *ABCFO* equations, suggesting that the increase in abnormal cash flows was significantly higher in firms with investment grade threshold ratings and minus-notch ratings than other rated firms. However, the increase in abnormal cash flows in *IGT* firms (*MNOTCH* firms) is statistically indistinguishable from that in non-rated firms as the sum of the coefficients on *RATED∗PostFC* and *IGT∗PostFC* (*MNOTCH∗PostFC*) is not significant at 10% (z-stats of 1.29 and 0.87, respectively). No significant change is observed in other real EM proxies in *IGT* or *MNOTCH* firms. Findings remain similar

[66] I do not test how real EM changed in *CWNEG* firms because real EM is generally not feasible within the credit watch period.

when restricting the definition of *IGT* to only the firms with the lowest investment grade rating. Finally, narrowing the pre-FC and post-FC period windows to two years or redefining the FC period as in deHaan (2017) provides similar inferences (untabulated).

[INSERT TABLE 3]

Table 4 Panel A presents the regression output from estimating the cash holdings model. *EXCASH* (the proxy for excess cash or cash surplus) comprises residuals from this regression. Panel B presents the results from the main tests where *EXCASH* is the dependent variable. I include main firm characteristics in Panel B regressions as well to control for any non-linear relationships that may exist between these variables and cash and short-term investments. Results suggest that rated firms held, on average, significantly less excess cash than non-rated firms in all periods. Importantly, although both rated and non-rated firms increased their excess cash holdings in the post-FC period, the increase was higher in rated firms (*RATED∗PostFC* significantly positive at 1% in all columns). The increase in the liquidity of firms with rating triggers was not significantly different from that in other rated firms, however (*RTR∗PostFC* not significant in column 2). One interesting result from Panel B is that in both the pre-FC and the post-FC periods *RTR* firms held less excess cash than other rated firms.

[INSERT TABLE 4]

I also examine whether firms placed under negative credit watch increase their liquidity to a greater extent in the post-FC period than in the pre-FC period. Although most credit watch placements start and get resolved within the fiscal year, credit analysts and firm managers privately communicate during this period. Therefore, firms can signal their intention to increase their liquidity by the end of the fiscal year for a successful resolution of the credit watch. To test this argument, I regress the change in *EXCASH*

(year-end excess cash minus beginning excess cash) on *CWNEG* and its interactions with *FC* and *PostFC* (rated firms sample only). In addition to the existing control variables, I include lagged *CASH*, lagged net working capital (*NETWC*), and *RATING* in the regression as firms with higher ratings and high level of liquidity may not need to increase their liquidity. I also control for the change in net working capital as it may be an alternative option to changing the firm's cash holdings.

Table 5 presents the results from this test. *CWNEG* has a negative but insignificant coefficient, suggesting that before the FC, the change in excess cash in firms placed under negative credit watch was similar to that in other rated firms. In the post-FC period, however, the increase in liquidity in *CWNEG* firms was significantly higher than that in other rated firms (alternatively, the decrease in liquidity was smaller in *CWNEG* firms than in other rated firms). Inferences do not change when industry fixed effects are included or excluded (column 1 versus column 2). Results do not appear to be driven by the deteriorating performance of *CWNEG* firms either, as the coefficients on the variables of interest and their z-statistics remain very similar when the change in ROA is included in the regressions (untabulated). In sum, results from multivariate tests suggest that the increase in rating quality does not seem to have prompted firms to manage real activities to influence their ratings, but instead led them to increase their liquidity.

[INSERT TABLE 5]

5.6 Conclusion

In this chapter, I examine whether firms managed real activities or increased their cash holdings in response to the increase in rating quality in the wake of the FC. I do not find strong evidence in support of firms using real EM to influence their ratings when CRAs tightened their rating standards. However, rated firms increased their liquidity to a

greater extent in response to higher rating quality than non-rated firms. The latter finding suggests that an increase in rating quality may impact not just a firm's reporting quality, but also real firm decisions. An interesting avenue for future research would be to investigate whether such cash accumulation is detrimental to long-term profitability (by restricting investment) or value-enhancing (through its effect on the firm's financial risk). Taken together, these results are consistent with the findings from the previous chapter that when rating standards improve, firms take actions that are likely to earn them a positive rating assessment from CRAs.

Appendix A: *Variable definitions*

Variables	Definitions
ABCFO	Performance-matched residuals from estimating the model of cash flows from operating activities (equation 1). Each industry-year group is required to have at least 12 observations. Industries are defined based on the two-digit SIC codes. Performance-matching is done by identifying the firm with the closest ROA within the same industry-year and differencing the abnormal cash flows from operations of the two firms. The same procedure is used when calculating the other real EM proxies.
ABDEXP	Performance-matched residuals from estimating the model of discretionary expenses (equation 3). Discretionary expenses is the sum of SG&A, R&D, and advertising expenses.
ABPROD	Performance-matched residuals from estimating the model of production costs (equation 2). Production costs is the sum of cost of goods sold and change in inventory.
ABSGA	Performance-matched residuals from estimating the model of SG&A expenses (equation 4).
ACQ	Acquisition expenditures divided by total assets.
ANAFOL	The number of equity analysts following the firm.
CAPEX	Capital expenditures divided by total assets.
CASH	Natural log of firm's cash holdings. Cash holdings are calculated as the cash and short-term investments divided by assets minus cash and short-term investments.
CFTCAPEX	Ratio of net cash flows from operating activities to capital expenditures.
CFTLIAB	Ratio of operating income before depreciation and amortization to liabilities.
CFVOL	Standard deviation of the firm's cash flows for the last ten years. Cash flows are calculated as operating income before depreciation and amortization minus interest, taxes, and dividends, divided by assets.
CHAIR	Indicator if the CEO is also the chair of the board.

Appendix A *(continued)***:** *Variable definitions*

CWNEG	Indicator for firms placed under credit watch at least once during the fiscal year.
DEBTIS	Issued debt minus retired debt, divided by total assets.
DIV	Indicator for firms that paid out dividends in the fiscal year.
EARNOP	Earnings before depreciation and amortization minus dividends, divided by total assets minus cash.
EXCASH	Residuals from estimating the model of cash holdings (equation 5).
EXTFIN	Indicator if the firm's free cash flow is less than -0.5. Free cash flow is calculated as the difference between earnings and total accruals less the average capital expenditures for the last three years, divided by average current assets.
FC	Indicator for the financial crisis period (years 2008 and 2009).
GROWTH	Percentage change in sales from year t-2 to year t-1.
IGT	Indicator for firms that have an S&P's (Moody's) issuer rating of BBB- (Baa3) or BB+ (Ba1). If the firm is rated by both agencies, S&P's issuer rating is used.
INDPERC	Percentage of independent directors on the board.
INST	Percentage of institutional holders.
LEV	Sum of short-term and long-term debt, divided by total assets.
MNOTCH	Indicator for firms that have an issuer rating of AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, or B3) from S&P (Moody's).
MTB	Market-to-book ratio, calculated as the book value of assets, less the book value of equity, plus the market value of equity, divided by assets (measured in t-1).
NEGNI	Indicator for firms that had negative earnings for the last two or more years.
NETWC	Working capital minus cash, divided by total assets minus cash.
PostFC	Indicator for the post-crisis period (years 2010 through 2012).
RATED	Indicator for firms that had an issuer rating in both the pre-FC and the post-FC periods.

Appendix A *(continued)***:** *Variable definitions*

RATING	Issuer rating from S&P (or Moody's when the firm is not rated by S&P). The variable equals zero if the firm does not have an issuer rating from either rating agency.
REVOLVER	Indicator if the firm acquired a revolving credit line facility with a maturity of at least 12 months in a given fiscal year.
ROE	Net income divided by equity.
RTR	Indicator for firms that have at least one debt contract with rating-based performance pricing provisions at the end of the fiscal year.
SIZE	Natural log of total assets.
WCAP	Working capital divided by total assets.
ZSCORE	Altman's Z-score (measured at t-1), calculated as $3.3 * \text{EBIT} / \text{TA} + \text{Sales} / \text{TA} + 1.4 * \text{Retained Earnings} / \text{TA} + 1.2 * \text{WCAP} / \text{TA} + 0.6 * \text{Market value of equity} / \text{Total Liab}$, where TA is total assets.

Appendix B: *Numerical values corresponding to S&P's and Moody's ratings*

Group	Numeric value	S&P rating	Moody's rating
Investment grade	21	AAA	Aaa
	20	AA+	Aa1
	19	AA	Aa2
	18	AA-	Aa3
	17	A+	A1
	16	A	A2
	15	A-	A3
	14	BBB+	Baa1
	13	BBB	Baa2
	12	BBB-	Baa3
Speculative grade	11	BB+	Ba1
	10	BB	Ba2
	9	BB-	Ba3
	8	B+	B1
	7	B	B2
	6	B-	B3
	5	CCC+	Caa1
	4	CCC	Caa2
	3	CCC-	Caa3
	2	CC, C	Ca
In default	1	D	C
Not rated	0		

Table 1: *Descriptive statistics*

	Rated firms					Non-rated firms				
	Pre-FC		Post-FC		Change	Pre-FC		Post-FC		Change
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
ABCFO	0.001	0.117	-0.004	0.105	-0.006	-0.006	0.194	-0.003	0.180	0.003
ABDEXP	-0.024	0.250	-0.019	0.249	0.005	0.022^{+}	0.395	0.019^{+}	0.383	-0.003
ABPROD	0.007	0.225	0.009	0.226	0.002	0.002	0.337	-0.005	0.382	-0.007
ABSGA	0.016	0.195	0.012	0.194	-0.004	-0.007^{-}	0.275	0.002^{-}	0.274	0.009
ACQ	0.032	0.074	0.023	0.055	-0.009^{a}	0.024^{-}	0.065	0.019^{-}	0.055	-0.005^{a}
CAPEX	0.061	0.060	0.052	0.053	-0.009^{a}	0.051^{-}	0.062	0.041	0.054	-0.010^{a}
CASH	-3.087	1.456	-2.840	1.467	0.247^{a}	-1.470^{+}	2.006	-1.433^{+}	1.886	0.037^{b}
CFTCAPEX	2.951	3.759	3.426	4.616	0.475^{a}	-2.497^{-}	28.164	-5.890^{-}	40.350	-3.393^{ab}
CFTLIAB	0.261	0.193	0.236	0.163	-0.025^{a}	0.018^{-}	1.667	0.079^{-}	1.928	0.061
CFVOL	0.044	0.085	0.042	0.053	-0.002	0.399^{+}	1.035	0.466^{+}	1.234	0.067^{a}
CWNEG	0.169	0.374	0.080	0.272	-0.089^{a}	-	-	-	-	-
DEBTIS	0.032	0.070	0.027	0.059	-0.005^{a}	0.024^{-}	0.089	0.017^{-}	0.057	-0.007^{a}
DIV	0.628	0.483	0.632	0.482	0.004	0.255^{-}	0.436	0.283^{-}	0.451	0.028^{a}
EARNOP	0.091	0.084	0.081	0.095	-0.010^{a}	-0.461^{-}	4.100	-0.539^{-}	5.150	-0.078
EXCASH	-0.383	1.330	-0.106	1.328	0.277^{a}	0.065^{+}	1.446	0.187^{+}	1.366	0.121^{ab}
IGT	0.163	0.369	0.186	0.390	0.023	-	-	-	-	-
INST	0.762	0.179	0.734	0.232	-0.028^{a}	0.499^{-}	0.307	0.508^{-}	0.324	0.009^{b}
LEV	0.311	0.220	0.331	0.196	0.020^{a}	0.134^{-}	0.368	0.119^{-}	0.182	-0.015^{ab}

Table 1 *(continued)***:** *Descriptive statistics*

MNOTCH	0.313	0.464	0.311	0.463	-0.002	-	-	-	-	-
MTB	1.748	0.775	1.509	0.607	-0.239[a]	2.773[+]	3.866	2.125[+]	2.073	-0.648[ab]
NETWC	0.043	0.132	0.047	0.133	0.004	-0.041[-]	1.150	-0.059[-]	1.207	-0.018
RATING	11.703	3.193	11.318	3.255	-0.385[a]	-	-	-	-	-
REVOLVER	0.522	0.500	0.470	0.499	-0.052[a]	0.155[-]	0.362	0.138[-]	0.345	-0.017[ab]
RTR	0.497	0.500	0.470	0.499	-0.027	-	-	-	-	-
SIZE	8.374	1.301	8.527	1.358	0.153[a]	5.054[-]	1.502	5.304[-]	1.564	0.250[a]
ZSCORE	3.118	2.410	2.581	1.827	-0.537[a]	6.843[+]	8.412	4.286[+]	7.146	-2.557[ab]

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. Rated firms are firms that had an issuer rating in a given fiscal year. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. The definitions of variables can be found in Appendix A.

Change is calculated as the change in variable mean from the pre-FC period to the post-FC period. [a] superscript indicates whether these changes are statistically significant at 5%. [b] superscript indicates whether the *Change* for the subsample of non-rated firms is significantly different from the *Change* for the subsample of rated firms. When [+] ([-]) superscript appears under "Mean" column, it indicates whether the variable mean for the subsample of non-rated firms in a given period (i.e. pre-FC or post-FC) is significantly greater (smaller) at 5% than the variable mean for the subsample of rated firms in that same period.

Table 2 – *Panel A*: *Post-FC real activities management in rated firms*

Dependent variable	*ABCFO*	*ABPROD*	*ABDEXP*	*ABSGA*
RATED	-0.039***	0.122***	-0.096***	-0.067***
	(-3.55)	(6.26)	(-3.14)	(-2.71)
PostFC	-0.005	-0.017*	0.039***	0.009
	(-1.10)	(-1.86)	(3.49)	(1.19)
RATED ∗ PostFC	-0.005	0.010	-0.010	-0.012
	(-0.69)	(0.64)	(-0.55)	(-0.66)
FC	-0.004	0.001	0.020*	0.005
	(-0.88)	(0.08)	(1.77)	(0.55)
RATED ∗ FC	0.004	-0.001	-0.003	-0.002
	(0.53)	(-0.03)	(-0.16)	(-0.08)
LEV	0.010	0.000	-0.096***	-0.176***
	(0.78)	(0.01)	(-3.17)	(-6.39)
SIZE	-0.008***	0.026***	-0.027***	0.029**
	(-4.48)	(6.31)	(-5.53)	(2.46)
GROWTH	-0.001	-0.030	0.000	-0.029*
	(-0.08)	(-0.81)	(0.00)	(-1.91)
MTB	0.003	-0.039***	0.051***	0.012***
	(0.89)	(-7.07)	(7.08)	(3.46)
RATING	0.003***	-0.011***	0.010***	0.009***
	(3.85)	(-7.24)	(4.03)	(5.40)
ZSCORE	-0.000	0.005***	-0.007***	-0.002
	(-0.52)	(3.54)	(-4.45)	(-1.48)
CFVOL	0.023***	0.007	-0.001	0.016*
	(3.34)	(0.42)	(-0.08)	(1.67)

Table 2 – *Panel A* *(continued)*: *Post-FC real activities management in rated firms*

WCAP	-0.025*	0.047*	0.003	-0.084***
	(-1.72)	(1.66)	(0.08)	(-3.49)
CFTLIAB	0.027***	-0.057***	0.008	-0.042***
	(3.84)	(-3.32)	(0.52)	(-2.96)
CFTCAPEX	0.002***	-0.000	0.001	0.001
	(5.71)	(-0.01)	(1.12)	(0.77)
ROE	-0.003	0.007	-0.015	0.001
	(-1.04)	(0.92)	(-1.64)	(0.09)
EXTFIN	0.039***	-0.009	-0.027	0.021
	(6.46)	(-0.85)	(-1.50)	(1.45)
NEGNI	-0.006	0.000	0.024	0.014
	(-0.62)	(0.01)	(1.35)	(1.09)
ANAFOL	0.002***	-0.002***	0.002***	0.001
	(6.12)	(-3.63)	(2.61)	(1.19)
INST	-0.010	-0.018	0.019	-0.003
	(-1.02)	(-1.03)	(0.76)	(-0.14)
CHAIR	-0.004	-0.000	0.001	0.006
	(-1.07)	(-0.01)	(0.15)	(1.02)
INDPERC	0.019	-0.104***	0.020	0.020
	(1.42)	(-3.93)	(0.59)	(0.75)
Observations	6154	6066	5471	5468
Adjusted R^2	0.068	0.049	0.044	0.035

Table 2 – *Panel B*: *Post-FC real activities management in firms with rating triggers*

Dependent variable	*ABCFO*	*ABPROD*	*ABDEXP*	*ABSGA*
RATED	-0.042***	0.121***	-0.088***	-0.065**
	(-3.13)	(4.99)	(-2.71)	(-2.57)
RTR	-0.006	0.002	-0.008	0.014
	(-0.68)	(0.12)	(-0.45)	(0.94)
PostFC	-0.005	-0.019**	0.044***	0.011
	(-1.10)	(-1.99)	(3.56)	(1.17)
RATED ∗ PostFC	-0.004	0.017	-0.019	-0.017
	(-0.33)	(0.87)	(-0.78)	(-0.77)
RTR ∗ PostFC	-0.004	-0.003	0.003	-0.001
	(-0.34)	(-0.16)	(0.13)	(-0.06)
FC	-0.004	-0.001	0.025**	0.006
	(-0.94)	(-0.15)	(2.03)	(0.75)
RATED ∗ FC	0.007	-0.011	-0.001	0.010
	(0.69)	(-0.55)	(-0.06)	(0.47)
RTR ∗ FC	-0.005	0.023	-0.016	-0.029
	(-0.50)	(1.07)	(-0.62)	(-1.51)
Observations	6019	5932	5368	5365
Adjusted R^2	0.068	0.048	0.043	0.035
z-stat for (RATED + RTR)	-3.36	4.73	-2.77	-2.05
z-stat for FC∗(RATED + RTR)	0.22	0.54	-0.74	-0.82
z-stat for PostFC∗(RATED + RTR)	-0.68	0.62	-0.65	-0.91

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RTR* equals one if the firm had at least one private debt contract that included a rating trigger at the end of the fiscal year, and zero otherwise. In Panel B, the sample size is smaller than that in Panel A because I exclude firm-year observations when the firm has a debt contract that includes a rating trigger but does not have an issuer rating.

ABCFO refers to abnormal cash flows from operations. *ABPROD* refers to abnormal production costs. *ABDEXP* refers to abnormal discretionary expenses. *ABSGA* refers to abnormal selling, general and administrative expenses. The definitions of all other variables can be found in Appendix A.

Since *RTR* is a subset of *RATED*, its interaction with *RATED* does not appear in the regression. For ease of reference, the z-statistics for the sum of *RATED* and *RTR* and for the changes in *RTR* subsample from the pre-FC to the FC and post-FC periods are presented below the regression output.

Table 3 – *Panel A*: *Post-FC real activities management in firms with investment grade threshold ratings*

Dependent variable	*ABCFO*	*ABPROD*	*ABDEXP*	*ABSGA*
RATED	-0.035**	0.127***	-0.099***	-0.078***
	(-2.46)	(4.85)	(-3.15)	(-3.44)
IGT	-0.016*	-0.011	0.008	0.028*
	(-1.83)	(-0.64)	(0.43)	(1.71)
PostFC	-0.005	-0.017	0.039***	0.008
	(-1.11)	(-1.61)	(3.27)	(1.16)
RATED ∗ PostFC	-0.010	0.007	-0.010	-0.009
	(-1.12)	(0.42)	(-0.41)	(-0.53)
IGT ∗ PostFC	0.025**	0.012	-0.004	-0.014
	(2.11)	(0.52)	(-0.13)	(-0.66)
FC	-0.004	0.001	0.020	0.005
	(-0.85)	(0.10)	(1.58)	(0.69)
RATED ∗ FC	-0.000	0.001	-0.001	0.005
	(-0.03)	(0.06)	(-0.06)	(0.25)
IGT ∗ FC	0.020*	-0.007	-0.009	-0.026
	(1.82)	(-0.26)	(-0.33)	(-1.29)
Observations	6154	6066	5471	5468
Adjusted R^2	0.068	0.049	0.044	0.035
z-stat for (RATED + IGT)	-3.63	3.80	-3.27	-1.91
z-stat for FC∗(RATED + IGT)	1.83	-0.21	-0.40	-0.98
z-stat for PostFC∗(RATED + IGT)	1.29	0.77	-0.48	-0.97

Table 3 – *Panel B*: *Post-FC real activities management in firms with minus-notch ratings*

Dependent variable	*ABCFO*	*ABPROD*	*ABDEXP*	*ABSGA*
RATED	-0.036***	0.135***	-0.123***	-0.087***
	(-2.93)	(5.03)	(-4.61)	(-3.50)
MNOTCH	-0.010	-0.021	0.046**	0.029**
	(-1.31)	(-1.29)	(2.53)	(2.16)
PostFC	-0.005	-0.017*	0.039***	0.009
	(-1.05)	(-1.68)	(3.18)	(1.16)
RATED ∗ PostFC	-0.011	0.009	-0.008	-0.019
	(-1.27)	(0.51)	(-0.37)	(-0.98)
MNOTCH ∗ PostFC	0.020*	0.004	-0.007	0.024
	(1.82)	(0.18)	(-0.27)	(1.43)
FC	-0.004	0.001	0.020	0.005
	(-0.83)	(0.08)	(1.64)	(0.66)
RATED ∗ FC	-0.001	0.003	-0.001	-0.003
	(-0.06)	(0.19)	(-0.03)	(-0.16)
MNOTCH ∗ FC	0.015	-0.011	-0.010	0.006
	(1.48)	(-0.47)	(-0.33)	(0.32)
Observations	6154	6066	5471	5468
Adjusted R^2	0.068	0.050	0.046	0.038
z-stat for (RATED + MNOTCH)	-3.61	4.30	-2.74	-2.17
z-stat for FC∗(RATED + MNOTCH)	1.53	-0.30	-0.35	0.11
z-stat for PostFC∗(RATED + MNOTCH)	0.87	0.56	-0.59	0.29

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *IGT* equals one if a firm's issuer rating is at the investment grade threshold (S&P's rating of BBB-/BB+ or Moody's rating of Baa3/Ba1), and zero otherwise. *MNOTCH* equals one if a firm has one of the following ratings from S&P (Moody's): AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, B3).

ABCFO refers to abnormal cash flows from operations. *ABPROD* refers to abnormal production costs. *ABDEXP* refers to abnormal discretionary expenses. *ABSGA* refers to abnormal selling, general and administrative expenses. The definitions of all other variables can be found in Appendix A.

Since *IGT* and *MNOTCH* are subsets of *RATED*, their interactions with *RATED* do not appear in the regressions. For ease of reference, the z-statistics for the sum of *RATED* and *IGT* (*MNOTCH*) and for the changes in these subsamples from the pre-FC to the FC and post-FC periods are presented below the regression output in Panel A (Panel B).

Table 4 – *Panel A*: *Determinants of firm's cash holdings*

Dependent variable:	CASH
MTB	0.129***
	(15.70)
NETWC	-1.357***
	(-30.80)
SIZE	-0.058***
	(-6.74)
EARNOP	-0.014
	(-0.98)
LEV	-2.643***
	(-31.17)
CFVOL	0.001
	(0.27)
CAPEX	-4.319***
	(-15.18)
ACQ	-3.621***
	(-18.26)
DIV	-0.330***
	(-14.25)
INST	0.419***
	(8.74)
ZSCORE	-0.107***
	(-7.09)
CFTLIAB	-0.000
	(-0.47)
CFTCAPEX	-0.399***
	(-14.96)
REVOLVER	1.229***
	(6.85)
DEBTIS	0.129***
	(15.70)
Industry FE	Yes
Year FE	Yes
Observations	14917
Adjusted R^2	0.579

Table 4 – *Panel B*: *Post-FC excess cash in firms with rating related incentives*

Dependent variable	EXCASH	
RATED	-0.147***	-0.158**
	(-2.76)	(-2.11)
RTR		-0.156**
		(-2.27)
PostFC	0.194***	0.184***
	(7.28)	(6.77)
RATED ∗ PostFC	0.264***	0.292***
	(3.21)	(3.20)
RTR ∗ PostFC		-0.026
		(-0.29)
FC	0.018	0.015
	(0.68)	(0.52)
RATED ∗ FC	0.011	0.006
	(0.11)	(0.05)
RTR ∗ FC		0.029
		(0.30)
MTB	0.047***	0.044***
	(6.41)	(5.98)
SIZE	-0.064***	-0.062***
	(-11.16)	(-10.07)
LEV	-0.628***	-0.626***
	(-10.10)	(-8.70)
CFVOL	0.000	0.001
	(0.08)	(0.13)
Observations	14917	14766
Adjusted R^2	0.035	0.035

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.
FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only the firms that appear in both the pre-FC and the post-FC periods. *RATED* equals one if a firm had an issuer rating in a given fiscal year, and zero otherwise. A firm is considered rated (non-rated) only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *RTR* equals one if the firm had at least one private debt contract that included a rating trigger at the end of the fiscal year, and zero otherwise.
CASH refers to the natural log of firm's cash holdings, which is calculated as the cash and short-term investments divided by assets minus cash and short-term investments. *EXCASH* is the residuals from estimating the cash holdings model in panel A. The definitions of all other variables can be found in Appendix A.

Table 5: *Change in excess cash in firms placed under negative credit watch*

Dependent variable:	ΔEXCASH	
CWNEG	-0.057	-0.092
	(-0.87)	(-1.51)
PostFC	0.156***	0.155***
	(5.04)	(4.55)
CWNEG ∗ PostFC	0.130*	0.132*
	(1.66)	(1.74)
FC	0.236***	0.236***
	(5.88)	(5.44)
CWNEG ∗ FC	0.131	0.088
	(1.32)	(1.12)
MTB	0.042	-0.005
	(1.25)	(-0.14)
$NETWC_{t-1}$	0.055	-0.124
	(0.44)	(-0.88)
$CASH_{t-1}$	-0.146***	-0.214***
	(-8.61)	(-11.88)
Δ*NETWC*	-0.709***	-0.730***
	(-3.13)	(-3.42)
SIZE	0.007	0.015
	(0.45)	(0.95)
EARNOP	-0.176	-0.115
	(-1.13)	(-0.76)
LEV	-0.072	0.072
	(-0.69)	(0.61)
RATING	-0.018**	-0.005
	(-2.47)	(-0.69)
ZSCORE	0.032***	0.032***
	(2.58)	(2.91)
REVOLVER	0.375***	0.385***
	(14.32)	(15.83)
Industry FE	No	Yes
Observations	4406	4406
Adjusted R^2	0.106	0.130

***, **, and * denote significance at 1%, 5%, and 10% (two-tailed), respectively. Standard errors are obtained via bootstrapping. z-statistics are provided in brackets.

FC period starts in January 2008 and ends in December 2009. The pre-FC and the post-FC (*PostFC*) periods cover the three years before and after the FC period, respectively. The sample includes only rated firms. Rated firms are the firms that had an issuer rating in a given fiscal year. A firm is considered rated only if it had an issuer rating in both the pre-FC and the post-FC (none of the) periods. *CWNEG* equals one if the firm was placed under negative credit watch during the fiscal year, and zero otherwise.

Δ*EXCASH* is the change in excess cash from the beginning to the end of the fiscal year. *EXCASH* is the residuals from estimating the cash holdings model in Table 4 Panel A. A firm's cash holdings is calculated as the cash and short-term investments divided by assets minus cash and short-term investments. The definitions of all other variables can be found in Appendix A.

Chapter 6

Conclusion

Following the intense regulatory scrutiny and public criticisms in the wake of the financial crisis, CRAs made numerous changes to their rating criteria, transparency, and internal controls to restore their reputation and satisfy new requirements. Despite ample evidence regarding the effects of these changes on rating quality, we still know little about their impact on rated firms. Consequently, this thesis investigates how the changes in the rating environment affected rated firms, and how firms responded to these changes.

In tests examining the impact of tighter rating standards on the use of ratings in debt contracts, I find that lenders decreased their use of rating triggers when the reliance on ratings had higher reputational costs, but retained their use of rating triggers in cases where rating quality likely improved to a greater extent. Tests on the impact of increased rating quality on loan spreads provide two insights. Consistent with higher rating quality and more likely downgrades in the post-FC period, firms facing a bigger increase in CRA scrutiny after the FC receive lower interest rates when the PP provision relies on ratings rather than accounting numbers. Also consistent with higher rating quality after the FC, rating changes move loan spreads to a greater extent through pricing grids in the post-FC period.

Having documented the impact of the increased rating quality on rated firms, I proceed to investigate how firms' behaviors changed in response to the increase in rating quality. I find that reporting quality decreased in rated firms (and firms with strong rating-related incentives) in the post-FC period, whereas real activities management remained similar. I also find evidence of increased liquidity in rated firms and firms with strong

rating related incentives in response to higher rating quality, suggesting a potentially positive impact of tighter rating standards on rated firms.

This thesis has several contributions to the existing literature. First, it is one of the first studies to provide evidence of lenders responding positively to the improvement in rating standards and incorporating the increased rating quality into different dimensions of loan contracts despite the damage to the reputation of credit ratings after the FC. In doing so, it demonstrates one channel through which higher rating quality affects rated firms. Second, to the best of my knowledge, it is the first study to empirically document firms' responses to an increase in rating quality. One of the main findings of this thesis is that an improvement in rating standards leads to an increase in misreporting, suggesting that overall rating quality may be hampered by a decline in rated firms' reporting quality. This finding has implications for the regulations that aim to improve overall rating quality. Finally, this thesis demonstrates that despite leading to a decline in reporting quality, tighter rating standards are also likely to prompt rated firms to increase their liquidity. Whether such a decrease in financial risk is detrimental to firm value (due to potentially lower investment) or value-enhancing is not addressed in this thesis, and provides an interesting avenue for research.

Appendix I: *Definitions of all variables used in the thesis*

Variables	Definitions
ABACC	Performance-matched residuals from estimating the total accruals model (equation 5). Total accruals are calculated as income before extraordinary items and discontinued operations minus operating cash flows from continuing operations. Each industry-year group is required to have at least 12 observations. Industries are defined based on the two-digit SIC codes. Performance-matching is done by identifying the firm with the closest ROA within the same industry-year and differencing the abnormal accruals of the two firms.
ABCFO	Performance-matched residuals from estimating the model of cash flows from operating activities (equation 1). Each industry-year group is required to have at least 12 observations. Industries are defined based on the two-digit SIC codes. Performance-matching is done by identifying the firm with the closest ROA within the same industry-year and differencing the abnormal cash flows from operations of the two firms. The same procedure is used when calculating the other real EM proxies.
ABDEXP	Performance-matched residuals from estimating the model of discretionary expenses (equation 3). Discretionary expenses is the sum of SG&A, R&D, and advertising expenses.
ABPROD	Performance-matched residuals from estimating the model of production costs (equation 2). Production costs is the sum of cost of goods sold and change in inventory.
ABSGA	Performance-matched residuals from estimating the model of SG&A expenses (equation 4).
ACQ	Acquisition expenditures divided by total assets.
ANAFOL	The number of equity analysts following the firm.

Appendix I *(continued)*: *Definitions of all variables used in the thesis*

BINRATTR	Indicator that equals one if the debt contract includes a rating trigger and zero if it includes an accounting-based PP provision. No value is assigned to the variable if the debt contract does not include any PP provision.
CAPEX	Capital expenditures divided by total assets.
CASH	Natural log of firm's cash holdings. Cash holdings are calculated as the cash and short-term investments divided by assets minus cash and short-term investments.
CFTCAPEX	Ratio of operating income before depreciation and amortization to capital expenditures (measured in t-1 for Chapter 3 analysis).
CFTCURLIAB	Ratio of operating income before depreciation and amortization to total current liabilities (measured in t-1).
CFTLIAB	Ratio of operating income before depreciation and amortization to total liabilities (measured in t-1 for Chapter 3 analysis).
CFVOL	Standard deviation of the firm's cash flows for the last five years. Cash flows are calculated as operating income before depreciation and amortization minus taxes, divided by assets.
CHAIR	Indicator if the CEO is also the chair of the board.
CWNEG	Indicator for firms placed under negative credit watch at least once during the fiscal year.
DEBTIS	Issued debt minus retired debt, divided by total assets.
DIV	Indicator for firms that paid out dividends in the fiscal year.
EARNOP	Earnings before depreciation and amortization minus dividends, divided by total assets minus cash.
EXCASH	Residuals from estimating the model of cash holdings (equation 5).
EXTFIN	Indicator if the firm's free cash flow is less than -0.5. Free cash flow is calculated as the difference between earnings and total accruals less the average capital expenditures for the last three years, divided by average current assets.

Appendix I *(continued)*: *Definitions of all variables used in the thesis*

FC	Indicator for the financial crisis period (years 2008 and 2009).
FIRMSIZE	Natural log of the borrower's annual sales.
GROWTH	Percentage change in sales from year t-2 to year t-1.
HIPUBD	Indicator if 80% or more of the firm's debt comprises bonds and notes.
HIZSCORE	Indicator if the borrower's Z-score is higher than the median Z-score of borrowers within the same rating notch in a given fiscal year.
IGT	Indicator for firms that have an S&P's (Moody's) issuer rating of BBB- (Baa3) or BB+ (Ba1). If the firm is rated by both agencies, S&P's issuer rating is used.
INDPERC	Percentage of independent directors on the board.
INST	Percentage of institutional holders.
INTDEC	Indicator if the loan contract includes an interest-decreasing pricing grid.
INTINC	Indicator if the loan contract includes an interest-increasing pricing grid.
INVBANK	Indicator if at least one lead arranger is identified as an investment bank, finance company, mutual fund or pension fund in Dealscan.
LEV	Sum of short-term and long-term debt, divided by total assets (measured in t-1 for Chapter 3 analysis).
LOANSIZE	Natural log of the loan amount (in millions).
MATURITY	Natural log of loan maturity (in months).
MNOTCH	Indicator for firms that have an issuer rating of AA-, A-, BBB-, BB- or B- (Aa3, A3, Baa3, Ba3, or B3) from S&P (Moody's).
MTB	Market-to-book ratio, calculated as the book value of assets, less the book value of equity, plus the market value of equity, divided by assets (measured in t-1).
NEGNI	Indicator for firms that had negative earnings for the last two or more years.
NETWC	Working capital minus cash, divided by total assets minus cash.
NUMOFAR	Number of lead arrangers in a loan syndicate.
NUMOFCOV	Number of financial covenants in a debt contract.

Appendix I *(continued)*: *Definitions of all variables used in the thesis*

NUMOFLEN	Number of total lenders in a loan syndicate.
NUMOFSWEEPS	Number of sweeps in a debt contract.
OPINC	Cash flows from operating activities divided by total assets.
OPINCADJ	S&P's adjustment to operating income divided by sales. The adjustment measure is calculated as deferred income taxes, minus income taxes, minus capitalized software costs, minus capitalized interest, minus finance division's income (finance division's revenue minus finance division's operating expense), minus 50% of preferred dividends, minus write-downs after tax for the retail industry, plus adjustment due to operating leases, plus S&P's core pension adjustment, plus S&P's core post-retirement adjustment, minus the decrease in LIFO reserves.
OPINCADJALT	Alternative definition of *OPINCADJ*; its calculation is similar to *OPINCADJ* but excludes the adjustments due to finance division's income, use of LIFO, and preferred dividends.
PostFC	Indicator for the post-crisis period (years 2010 through 2012).
PP	Indicator if the debt contract includes a performance pricing provision.
PUBDEBT	Indicator for borrowers that issued public debt in the post-FC period.
RATED	Indicator for firms that had an issuer rating in both the pre-FC and the post-FC periods.
RATING	Issuer rating from S&P (or Moody's when the firm is not rated by S&P). In multivariate tests, the variable takes the value of zero if the firm does not have an issuer rating from either rating agency.
RATTR	Indicator if the debt contract includes a rating trigger.
REFIN	Indicator if the loan refinances a prior deal.
REL	Indicator if the lead arranger of the loan has been a lead arranger for any of the loans taken by the same company within the last five years (i.e., if the lead arranger is a relationship bank).
REVOLVER	Indicator if the loan is a revolving credit line.
ROA	Net income divided by total assets.

Appendix I *(continued)*: *Definitions of all variables used in the thesis*

ROE	Net income divided by equity.
RTR	Indicator for firms that have at least one debt contract with rating-based performance pricing provisions at the end of the fiscal year.
SECURED	Indicator if the loan is secured.
SIFI	Indicator if at least one of the lead arrangers was a systemically important financial institution during or immediately after the FC.
SIZE	Natural log of total assets.
SPREAD	Loan spread over LIBOR.
STAYIN	Indicator for firms that took a loan in both the pre-FC and the post-FC periods.
WCAP	Working capital divided by total assets (measured in t-1).
ZSCORE	Altman's Z-score (measured at t-1), calculated as $3.3 * \text{EBIT} / \text{TA} + \text{Sales} / \text{TA} + 1.4 * \text{Retained Earnings} / \text{TA} + 1.2 * \text{WCAP} / \text{TA} + 0.6 * \text{Market value of equity} / \text{Total Liab}$, where TA is total assets.

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