Bangor University

DOCTOR OF PHILOSOPHY

The Credit Rating Industry under New Regulatory Regimes

The Case of Financial Institutions

Jones, Laurence

Award date:
2019

Awarding institution:
Bangor University

The Credit Rating Industry under New Regulatory Regimes: The Case of Financial Institutions

By Laurence Jones

PhD thesis

BANGOR UNIVERSITY

Declaration and consent

I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.

Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw'r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o'r blaen ar gyfer unrhyw radd, ac nid yw'n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy.

Signature: Laurence Jones
Date: 13/02/2019

Abstract

The dominant role of credit ratings, along with the failure of important FIs, exacerbated the 2008 crisis and caused further damage to European economies, which highlighted the need for effective regulation to prevent a reoccurrence. This thesis investigates the effect of EU and US recent regulatory reforms of the rating industry on the quality of credit ratings of financial institutions (FIs), as well as the impact of the new EU financial regulatory initiatives on the performance of FIs.

The first empirical Chapter focuses on the EU reforms of credit rating agencies (CRAs) and provides evidence supporting the presence of a conservative rating bias in the post regulatory period, as increased scrutiny, fines and liability increase the cost of over rating. CRAs exhibit an unwarranted decrease in EU FI ratings, evidenced by an increase in false warning and a fall in the informativeness of FI rating downgrades in the post regulatory period. A subsequent rise in stock market responses to rating upgrades is consistent with CRAs expending greater effort to ensure they are justified. The second empirical Chapter focuses on the US reforms of CRAs and reports no significant impact on FI ratings, rather each CRA has responded differently to the passage of the US Dodd-Frank Act (DFA). There is, however, a significant reduction in stock market reactions to FI credit rating signals, consistent with diminishing reliance on credit ratings by market participants in the US. The third empirical Chapter builds and estimates a dynamic model of FI behaviour using discrete choice dynamic programming (DCDP). The model is used to simulate and examine the impact of regulations, including EU reforms of CRAs, capital adequacy regulation (Basel III), and the bail-in regime, on FIs' behaviour in the real economy. The results show that the shift to increasingly conservative rating behaviour triggered by the CRA reforms has caused FIs to respond by manipulating their capital ratios and to reduce lending activities. The results also show that more stringent capital requirements stimulate FIs to hold more capital, reduce lending and reveal a positive influence in reducing bank insolvency rates, particularly during the crisis period. The introduction of a bail-in regime reveals similar results, but crucially stimulates the adoption of a stable equilibrium (unlike Basel III).

This thesis highlights drawbacks with the current regulatory reforms of the EU and US FI rating industries and suggests potential solutions. The thesis also informs the policy debate surrounding the best way to regulate both CRAs and FIs and ensure that there is not a reoccurrence of the problems present in the 2008 financial crisis.

Acknowledgements

I would like to thank my supervisors, Dr Rasha Alsakka and Dr Noemi Mantovan, for all their help and support over the last three years. They have been the best supervisors I could have hope for and their encouragement, patience and effort has been invaluable throughout the PhD. I would also like to thank Professor Owain ap Gwilym for replacing my supervisors when they were away and being an invaluable source of expertise.

I would also like to thank all the staff and students who I have met during my time at Bangor Business School who have made it a pleasure to study here. A special thanks to my friends who have been very supportive and encouraging of my studies.

Thanks to family for supporting me and in particular thanks to my wife for helping me to succeed. I would like to thank both my parents for their encouragement and help over the last three years and especially my dad, who has given me great feedback on my work.

Contents

List of tables

List of supporting tables

List of figures

List of supporting figures

Introduction

Chapter 1

1.1 INTRODUCTION

The US sub-prime crisis led to increased public and regulatory scrutiny of the quality of ratings issued by credit rating agencies (CRAs) (e.g. Bae et al., 2015; Flynn and Ghent, 2018). The key aim of the thesis is to investigate the impact of the EU and US regulatory reforms on the quality of the ratings of financial institutions (FIs). The thesis also aims to build and estimate a dynamic model of European bank behaviour and to utilise the model to simulate and examine the impact of various regulatory reforms (including CRA regulation, bail-in regime and capital adequacy requirements) on FI's behaviour.

High quality ratings are vital for the proper functioning of the financial system, given that credit ratings are relied on by regulators, debt issuers, investors and financial institutions[1] (FIs) (Becker and Milbourn, 2011; EC, 2016). Inflated ratings (overstatements of creditworthiness, see Section 2.2.1) mislead the market about the true financial condition of a debt issuer. It is now evident that inflated ratings (especially in structured finance products e.g. RMBs, CDO, etc, see Section 2.2.10) were prevalent prior to the global financial crisis, with the most notable example being Lehman Brothers' AAA rating months before its financial collapse.

In response to the sub-prime crisis, both the EU and the US enacted reforms of the rating market. The EU enacted three key reforms, CRA I in September 2009 to address conflicts of interest in the ratings proves through CRA disclosure requirements. This is followed by CRA II in July 2011 which established a new regulatory body, the European Securities and Markets Authority (ESMA), to enforce the regulation, and CRA III in May 2013 which instigated a new civil liability regime liability for CRAs along with an expansion of the transparency and monitoring requirements (see Section 2.3.2). The US passed the Dodd-Frank Act (DFA) in July 2010 that brought in reforms requiring increased disclosure and monitoring of CRAs by the SEC (see Section 2.3.3).

Further, the 2008 financial crisis led to the collapse and restructuring of numerous important financial institutions, which exacerbated the crisis and caused further damage to European economies. Recent European regulatory efforts have therefore sought to reform the banking industry and to mitigate FI risk-taking behaviour to prevent a future re-occurrence, which include, in addition to the reforms of CRAs, a European bail-in regime, capital adequacy requirements (Basel III). The EU established the Bank Recovery and Resolution Directive

[1] In this thesis the terms bank and FI are used interchangeably.

(BRRD), which contains provisions for a bail-in mechanism from 2015 and aims to shift the burden of FI failure from the taxpayer to equity holders and bondholders (see Section 2.4.4). Basel III increases the level of equity held by FIs and as a result means that they stand to lose more in the event of insolvency (see Section 5.6.2).[2]

To the best of my knowledge, this is the first study to investigates whether the new EU and US CRA regulations have achieved their stated objectives in FI rating sector (see Sections 2.3.4 and 2.3.5). FIs were at the centre of the recent 2008 financial crisis and the widespread presence of rating inflation in the FI rating market acted to exacerbate the crisis. Ensuring that the reforms of the FI rating industry are successful is of vital importance to help prevent a reoccurrence of the same problems that led to the 2008 crisis.

The thesis is also unique in estimating a dynamic model of European FI behaviour and using the model to simulate and examine the impact of various on FI's performance. In particular, the model is used to examine the link between credit ratings and FI behaviour (particularly FI capital structure decisions) and how regulatory reforms affect the relationship. Bank capital structure and risk-taking behaviour is at the heart of the regulatory debate, with much effort expended by regulators trying to curb risk taking behaviour. Chief among these efforts are the enactment of the Basel reforms (Basel II and III, see Section 2.4.1) and the instigation of new Bail-in mechanisms (see Section 2.4.4). While there is a well-established link between credit ratings and FI capital structure (Kisgen, 2006 and see Section 2.4.2), to best of my knowledge, there is no research on how the regulation (in particular CRA reforms) have affected this relationship.

Ensuring financial stability is a vital topic, given FI's crucial influence on the real economy, hence the debates on the design of regulatory regimes are not yet settled. This thesis contributes to the understanding of the impact of regulation upon FI's decision-making and the consequences for the real economy.

The thesis answers three research questions. Firstly, what is the impact of the EU regulatory reforms on the quality of EU FI ratings (see Chapter 3)? Secondly, what is the impact of the US regulatory reforms on the quality of US FI ratings (see Chapter 4)? Thirdly, what is the impact of recent regulatory reforms (in particular the rating market) on FI behaviour and risk taking in the EU (see Chapter 5)? Additionally, Chapter 5 builds and estimates a dynamic

[2] A new total common equity capital ratio (CET1) requirement of 4.5% with an additional capital conservation buffer of 2.5%, bringing the total common equity ratio to 7.0% (see Section 5.6.2).

model of FI behaviour and uses this model to simulate counterfactual scenarios in which these three key regulatory reforms are implemented prior to the financial crisis, thereby enabling investigation of the resultant impact on FI's performance, risk and lending activity.

Chapters 3 and 4 examine the EU and US reforms of FI rating market respectively, using panel datasets of 758 EU and 454 US FIs rated by S&P, Moody's and Fitch from 1st January 2006 to 1st June 2016 and 1st January 2005 to 1st June 2016, respectively. The regulations' principle purpose in both markets is to reduce the presence of rating inflation and increase rating quality. Hence, if successful this would result in a warranted decrease in rating levels and make ratings more informative. Therefore, Chapters 3 and 4 examine three aspects of ratings. Firstly, rating levels which should fall if there is a reduction in rating inflation (as these unwarranted high ratings are downgraded). Secondly, the incidence of false warning or unwarranted downgrades, which will reflect whether any change in rating levels is warranted by FI characteristics. Lastly, the informational content of rating announcements is examined by measuring the stock market reaction to FI credit rating signals.

The thesis tests three competing hypotheses regarding the channels the regulatory reforms can act through, namely the *disciplining*, *conservatism* and *reputation* hypotheses (see Sections 3.3 and 4.3). The *disciplining hypothesis* states that the regulation succeeds in the objective of increasing rating quality, on the grounds that increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring (Bae et al., 2015; Dimitrov et al., 2015). The regulation also promotes the disclosure of conflicts of interests, strengthening of CRAs' internal control structures and increased transparency. Secondly, *rating conservatism* argues that CRAs expose themselves to greater scrutiny, fines and potential liability by over-rating (less conservative) than under rating (more conservative) (Bannier et al., 2010). As a result, if increased scrutiny, fines and a CRAs liability for its ratings increase, this will cause a CRA to shift to more conservative rating behaviour to avoid the increased repercussions of over rating. The resultant shift to lower ratings will then not be due to more accurate ratings or a reduction in inflation, but rather by an unjustifiable decrease in rating levels to avoid the increased repercussions.[3] Significantly, this effect should only vary with increased regulatory stringency (i.e. the regulation) and opacity and not vary with reputational concerns. Lastly, *reputation hypothesis* states that CRAs

[3] FIs provide a good setting for which to measure this conservative bias, as it should be stronger for more opaque firms (Bannier et al., 2010) and FI are more opaque than corporates (Flannery et al., 2013; Iannotta, 2006; Morgan, 2002).

may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FI's financial characteristics to protect and rebuild their reputation (Bedendo et al., 2018; Flynn and Ghent, 2017; Becker and Milbourn, 2011). Crucially, if *reputation hypothesis* is present, its effect should be stronger in markets where CRAs care more about their reputation, i.e. stronger reputational concerns, as they will go to greater lengths to protect their reputation in such markets (Becker and Milbourn, 2011). Fortunately, the three hypotheses produce different testable predictions with regards to three key indicators of FI rating quality: rating levels, the number of false warnings and the informational content of rating announcements (see Section 3.3.4).

The third aim of the thesis is to evaluate how the reforms of the rating industry and other FI regulation have affected FI behaviour. FI behaviour is inherently dynamic, presenting complex mechanisms. Moreover, FIs behaviour is shaped by their expectations about the future, hence a static or reduced form framework is not suitable. An appropriate method is to employ a dynamic model which can capture and explain the underlying mechanisms. Hence, Chapter 5 builds and estimates a dynamic model using discrete choice dynamic programming (DCDP) and the simulated method of moments (SMM) (see Section 5.4). This model allows for the explicit inclusion of the interrelationship between key FI variables (e.g. credit ratings impact on cost of debt and cost of debt on financing decisions). It also allows for a closer examination of how the changing relationship impacts FI decision making, not only for directional but also for quantitative measurements of the magnitude of the effect of changes. By explicitly incorporating the theoretical model into the empirical analysis a measure of confidence (standard errors) of the results is included and ensures that the model fits the actual data.

The other advantage of this methodology is that it enables the simulation of counterfactual regulatory scenarios. This provides an ideal testing ground to examine how the implementation of the new regulation could have impacted FI behaviour during the 2008 and EU sovereign debt crises. Once the model has been estimated with the data, four counterfactual scenarios are examined. Firstly, the implementation of the bail-in in 2005 (modelled by increasing the theoretical cost of insolvency). Secondly, the implementation of the Basel III capital requirements in 2005. Thirdly, varying the level of *rating conservatism* (lower or higher rating levels) in 2005 (as Chapter 3 shows that the EU reforms have resulted in increased *rating conservatism*). Lastly, varying the market sensitivity to credit ratings (modelled by varying how sensitive FI's cost of debt is to credit ratings) as both the EU and US exhibit reduced market reactions to rating announcements.

The results from the empirical investigations and their key implications are as follows. Firstly, the results of Chapter 3 show that the recent EU regulatory actions have largely been successful in reducing rating inflation and have led to a significant decrease in rating levels. However, the evidence indicates that increased regulatory scrutiny, penalties and liability has caused an increase in *rating conservatism* as CRAs shift to increasingly conservative rating behaviour. This is evidenced by significantly lower rating levels, a significant increase in false warnings (unjustified downgrades), which in turn contributes to an observed decrease in the market reactions to rating downgrades (less informative downgrades). Additionally, there is evidence of an increase in rating upgrade informativeness, as CRAs expend greater effort to ensure that each upgrade is warranted. The results also confirm that the May 2013 regulatory update acted to strengthen the existing effect of the regulation. These results contrast with evidence from the US corporate rating market where the regulatory reforms of Dodd-Frank Act are making CRAs more protective of their reputation (*reputation hypothesis* dominates).[4]

Secondly, the results from Chapter 4 show that DFA has an overall insignificant effect on the US FI rating industry. However, each CRA (S&P, Moody's and Fitch) has responded differently in the post-DFA period. S&P's FI rating levels appear unaffected by the US regulation, while Moody's FI are significantly lower and Fitch FI ratings are significantly higher in post-DFA period. There is no evidence of a change in false warnings and no evidence in any differences with reputational concerns, which would imply that *rating conservatism* and *reputation hypothesis* can be rejected. This contrasts with evidence from the US corporate rating market where *reputation hypothesis* is driving the changes in CRAs' rating practice and from the EU FI rating market whereby increased *rating conservatism* dominates. The conclusion is that the DFA has led to a change in FI rating practices that is different for each of the three CRAs (see Section 4.5). There is evidence of a dampening in market reaction to rating changes which is indicative of the stock market placing less importance on the value of FI credit ratings.

The results of Chapter 5 show that FIs compensate for changes in CRA practices via the manipulation of their capital ratios and their actions in the debt/deposit markets. Any systematic change in rating practices (as in the case of the EU regulatory reforms) adds to FIs uncertainty and trigger a reduction of their lending activities. Increased leniency on the part of CRAs may result in increased FI insolvency rates as FIs take advantage of the higher ratings

[4] Studies have not found any evidence of increased *rating conservatism* or *disciplining hypothesis* in the US corporate rating market (see Section 3.2) in post DFA period.

by reducing their capital ratios. FIs also respond to changes in market sensitivity to FI ratings by reducing lending, varying their decision to solicit a rating and their sensitivity to the EU sovereign debt crisis, by expending more or less effort to maintain their ratings. The results show that more stringent capital requirements lead to a stronger increase in FI capital ratios that is driven by a fall in debt and results in increased FI stability. There is evidence of diminishing returns with the effect of capital ratios on FI insolvency rates. FIs shift away from lending activities to maintain profit levels (which fall due to reduced leverage). The implementation of the bail-in regime in the model leads to the adoption of higher optimal capital ratios, decrease FI insolvency in crisis periods and a shift away from lending to maintain profit levels. The effect from the bail-in is smaller than that of the capital requirements, but crucially results in a new equilibrium unlike the latter.

In general, the recent regulatory reforms of the FIs and FI rating industry sort to mitigate risk taking and enhance FI stability and transparency. Much is still unknown about the impact and effectiveness of these reforms. Hence, this thesis seeks to expand the understanding about the nature of these reforms and how they, along with capital requirements and the bail-in, have impacted FI behaviour. Therefore, this thesis contributes to the literature in four key aspects. Firstly, the thesis furthers the debate surrounding the most appropriate mechanisms for regulating CRAs in the future by providing a better understanding of the way in which EU regulatory reforms (CRA I, II and III) have impacted the FI rating industry. Secondly, the thesis provides an insight into the way the US regulatory reforms (Dodd-Frank Act) has affected the US FI rating industry. Thirdly, this is the first time dynamic structural estimation modelling has been applied to study FI behaviour and is, to the best of my knowledge, the first time that discrete choice dynamic programming has been implemented in the literature of corporate finance and banking. Lastly, utilising a dynamic model provide insights on how the subsequent CRA regulatory reforms in the EU, the new capital requirement regulation and the EU Bail-in regulation are affecting FI behaviour in real economy.

The thesis is structured as follows. Chapter 2 reviews the literature on credit ratings, banks and structural estimation. Chapter 3 investigates the impact of the EU reforms on the quality of FI ratings. Chapter 4 examines the impact of the US regulatory reforms on the quality of FI ratings. Chapter 5 builds and estimates a dynamic model of European FI behaviour and uses it to examine the impact of the various regulatory reforms on FI’s performance, risk and lending activity. Chapter 6 concludes.

Literature review

Chapter 2

2.1 INTRODUCTION

The aim of this Chapter is to lay out the current research relevant to the thesis; (i) the nature of credit rating agencies (CRAs), along with features and criticisms of the rating industry, (ii) the nature of the EU and US regulatory reforms of the CRA industry, (iii) features of the banking industry and how they are impacted by credit ratings and (iv) dynamic modelling techniques appropriate for modelling banks.

It is a well-established fact that investors react to the information provided by credit ratings (Hand et al., 1992; Holthausen and Leftwich, 1986; Dichev and Piotroski, 2001; Alsakka et al., 2015; Dimitrov et al., 2015) and that the flow of information throughout the financial system is helped by ratings. Demonstrating this Kliger and Sarig (2000) show that stock and bond prices are affected by changes to their ratings, which indicates that the ratings contain valuable information that cannot be easily found elsewhere. However, it has been shown by numerous papers (Skreta and Veldkamp, 2009; Bolton et al. 2012; He et al., 2012; Griffin and Tang, 2011; Opp et al., 2013) that since the introduction of the current "issuer pays" model in 1974, CRAs sometimes issue biased ratings.

The "issuer pays" model means that issuers (companies or governments) that wish to solicit a rating pay the CRA a fee and it is then published openly where investors may observe it free of charge. This has become the dominant business model in the industry despite attempts to establish alternative "subscription" based models. However, there is an inherent conflict of interest in the issuer pays business model, whereby the CRA may seek to attract clients by inflating ratings. This has been brought into sharp focus during the 2008 financial crisis where the rapid growth in structured finance products in the years prior led to growth in the credit rating industry, e.g. Moody's profits tripled between 2002 and 2006 (Bolton et al., 2012). It is possible that this rapid expansion led to reduced scrutiny and rating standards, as it is now known that many financial products rated in the lead up to the 2008 financial crisis were overvalued (Coffee, 2011).

There have been two apparent trends in rating behaviour in recent times. Firstly, CRAs were known to have inflated the rating of structured finance products in the years leading to the 2008 financial crisis, for which they have been widely criticised (Mason and Rosner, 2007). Secondly, there appears to have been a shift to assigning more conservative corporate credit ratings over the last twenty years. Baghai et al. (2014) demonstrate this, showing that, holding firm characteristics constant, average corporate ratings have dropped by three notches (e.g. A+ to BBB+) over the period 1985 to 2009.[5] They also find that the default rates, for both investment and non-investment grade, have declined over time (counter to the decrease of ratings). This supports the assertion of Baghai et al. (2014) that this decrease in rating may not be fully warranted. This thesis focuses on bank ratings which sit at the juncture of the two groups[6] and are less well understood.

In response to CRAs role in the 2008 financial crises, the regulators in the EU and US implemented new regulation. In the EU three pieces of regulation were enacted: Firstly, CRA I in September 2009 which established the initial wave of regulation, secondly, CRA II in July 2011 which charged the newly established ESMA for responsibility of supervising and certifying CRAs operating in the EU and thirdly, CRA III in the May 2013 which instigated a new civil liability regime and a strengthening of the existing regulation. In the US the Dodd-Frank Act was instigated in July 2010 and brought in regulatory reforms (see Section 2.3). Both the EU and US aimed at reforming the rating industry and to address the numerous issues including competition, conflict of interest, transparency and liability (see Section 2.2). The subsequent European sovereign debt crisis once again renewed scrutiny and highlighted the role, and power, that CRAs have in the global economy. Studies (Vu et al., 2017; Alsakka and ap Gwilym, 2013; Lane, 2013; Santis, 2013; Afonso et al., 2012) have begun to break apart and examine CRAs role and how they acted to exacerbate the crisis. While EU regulators brought in a regulatory update (CRA III) to further strengthen the regulatory reforms. This thesis examines the impact that these recent regulatory developments have on CRAs rating practices, the bank rating market and consequently on bank behaviour.

The Chapter is laid out as follows: Section 2.2 examines the literature on problems and criticism with the rating industry, Section 2.3 examines the EU and US regulatory reforms, Section 2.4 examines the banking industry and how credit ratings play a role, Section 2.5 examines structural modelling in finance and banking and Section 2.6 concludes.

[5] The shift to more stringent ratings could be down to increased regulatory scrutiny. Alp (2013) examines the variation in corporate credit ratings standards from 1985 to 2007, whereupon they observe a divergent pattern between investment (which appear to tighten) and speculative (which appear to loosen) grade ratings standards up to 2002. Then in 2002, there was a structural shift towards increasingly stringent ratings. Alp (2013) finds that, holding characteristics constant, there was a drop of 1.5 notches in ratings due to the tightening regulatory standards. Dimitrov et al. (2015) suggest that this could be down to increased investor criticism and regulatory scrutiny following the collapse of Enron and WorldCom.

[6] Corporate and structured finance ratings.

2.2 CRITICISM AND PROBLEMS WITH CRAS

There is much literature (see Table 2.1 and Table 2.2) studying the inherent problems with the issuer pays business model, not least of which are issues of competition, conflicts of interest and reputational concerns. Other issues that arise with CRA business practices include a lack of transparency, unconscious bias, liability and methodological issues.

2.2.1 CONFLICTS OF INTEREST AND THE CRA BUSINESS MODEL

The business model adopted in the CRA market is that of the "issuer pays" model,[7] where the issuer must pay to solicit a rating.[8] Issuers can be assumed to prefer favourable over truthful ratings and since it is the issuer who pays the CRAs fees there is an inherent conflict of interest (Boylan, 2012; Bolton et al., 2012).[9] Another factor that exacerbates the problem, is that many CRAs offer advisory services where issuers are schooled on how to structure debt to obtain higher ratings. This encourages issuers to make numerous small changes to complex financial products, which enables them to achieve artificially high ratings.

CRAs argue that the main incentive for them, to provide honest and accurate ratings, is their concern for their reputation (Cantor and Packer, 1997; Smith and Walter, 2002). This claim, that CRAs protection of their reputation keeps their ratings accurate and unbiased, is investigated by Mathis et al. (2009). They show that this reputation argument only applies when an adequately sized fraction of the CRA's income is from sources other than rating complex financial products.

Several academic studies argue that CRAs possess "reputational capital" (Bedendo et al., 2018; Coffee, 2011; Mathis et al., 2009; Coffee, 2006), whereby CRAs may build up their reputation by rating accurately, so that in the future they can inflate ratings when it suites them to gain enhanced revenues. Coffee (2011) argues that CRAs can continue to hold reputational capital as long as the barriers to entry are high and CRAs legal liability remains low.

[7] There is an exception that of Egan-Jones who is entirely investor supported (subscriber pays model) and was awarded NRSRO status on 21st December 2007. Egan-Jones were notable the first CRA to downgrade WorldCom and Enron (Egan-Jones, 2002).
However, recent events where Egan-Jones was banned from rating sovereigns, have called into question the merits of their business practices (Bloomberg, 2013).
[8] Solicited and unsolicited ratings are discussed in Section 2.2.2.
[9] Whereby CRAs may be tempted to inflate ratings to please issuer (rating inflation).

Becker and Milbourn (2011) expand on the study by Klein and Leffler (1981), who argue that building reputation can improve the ratings quality in markets where the presences of informational problems would otherwise act to prevent this. In a normal setting, customers (issuers) care about quality, but in the setting of CRAs they purchase the rating prior to assessing the quality (as the rating has yet to be performed) so this cannot factor into the purchase decision. It is possible, however, because of prior sales, to assess the quality in the past and hence a CRAs reputation, which can lead to a high rating quality equilibrium. In this "reputational equilibrium" the CRA may be induced to provide high quality ratings, when the value of predicted future revenue from maintaining the reputation exceeds any short term gains for providing poor quality (or inaccurate) ratings (Becker and Milbourn, 2011; Klein and Leffler, 1981).

2.2.1.1 Alternatives to the issuer pays model

Since the issuer pays business model has been criticized for the inherent conflicts of interest, alternative business models have been proposed. Deb and Murphy (2010) suggest that a return to the pre-1970s investor pays model (subscriber pays) would help resolve the problem of conflict of interest. However, they highlight the problem of "free-riding",[10] with the outcome that they would be a lack of sufficient revenue for CRA. To solve this problem, they propose that a government subsidiary be used to help supplement the cost of the ratings, this would be funded by a small tax that would be levied on issuers (or at the point of issue). Deb and Murphy (2010) conclude that this would "align the incentives of [CRAs] with investors" and make sure that it is still commercially viable for CRA.

Counter to this, Bongaerts (2014) argues that investor paid CRAs are faced with three sources of free riding[11] and as a result are not economically viable (compared with issuer paid CRAs). Bongaerts (2014) notes other alternatives including investor produced ratings and CRA co-investments (which uses "skin in the game" to induce better accuracy). However, Bongaerts (2014) concludes that since traditional issuer paid CRAs cater best to issuers and alternatives do not generate sufficient demand, and are often implemented ineffectively, it is unlikely to change. They stipulate that as a result the issuer pays model has and will continue to dominate the rating landscape.

[10] Where some investors avoid paying the fees and the burden of payment rests on a limited number.
[11] Free riding by issuers, investors and issuer-paid CRAs (see Bongaerts, 2014).

Payne (2014) argues that three possibilities include: (i) the existing subscriber pays model, where investors hire the CRAs, (ii) a modification to the current issuer pays system, where the issuer continues to pay, but an independent body (perhaps governmental) selects the CRA to perform the service (maybe randomly or based on performance) and (iii) a new independent CRA (perhaps government funded) to perform the rating instead of, or as well as, the issuer pays CRA.

With regards to credit ratings, there is no real alternative. One suggested alternative, credit default swap spreads, could at best provide only a partial substitute to the role of credit ratings (Coffee, 2011). A world without credit ratings is unrealistic as many financial industries, including the mortgage industry, rely on credit ratings to create a viable market for asset backed securities, e.g. RMBS (Retail mortgage backed securities). In-house financial analysis is not a viable standalone alternative for many smaller investment firms to the information provided by CRAs due to the nature and complexity of the financial products that they invest in. As such, at the current time simply discarding credit ratings is in no way feasible, they should be used in combination with in-house risk assessments (as recent EU and US regulation is attempting to promote).

2.2.2 SOLICITED AND UNSOLICITED RATINGS

Ratings can be both solicited (purchased) and unsolicited (not asked for). Fulghieri et al. (2013) examine the CRA's reputation and the role it plays, focusing on the role and impact of solicited and unsolicited ratings. They show that the issuance of unfavourable and unsolicited ratings gives CRAs the ability to extract higher fees from issuers (in effect punishing those companies that do not solicit a rating). Peculiarly, this acts to *strengthen* a CRAs reputation as it "demonstrates to investors that they resist the temptation to issue inflated ratings" (Fulghieri et al., 2013). As would be expected, they find that unsolicited ratings are lower than those that were solicited.[12] However, they show that, under certain conditions, a system that can include both unsolicited and solicited ratings lead to a more stringent rating standard. Their model is however not backed up with any empirical data, it would be beneficial if they could incorporate some to test their propositions.

[12] The lower ratings could be due to the information difference between solicited and unsolicited ratings, as a lack of information could stimulate strategic conservatism (see Bannier et al., 2010).

Byoun (2014) constructs a theoretical model which predicts that in the case of the issuer pays scheme CRAs have strong incentives to selectively issue unsolicited ratings to induce an increased number of fee-based solicited ratings. With respect to the information revealed by solicited and unsolicited ratings, Byoun (2014) finds that under the subscriber-fee business model a firm's quality was revealed by unsolicited ratings. Conversely, under the issuer pays model high quality firms are shown through solicited ratings and low-quality firms are shown through unsolicited ratings. Once again, it would have strengthened their case if they had incorporated some empirical data into their model and hence while Byoun (2014) demonstrates there was an effect but did not manage to quantify the scale of the effect.

This inherent differences between solicited and unsolicited ratings raises the question as to whether they are inherently biased. The historical view has been that unsolicited ratings have been downward biased (Bongaerts et al., 2012). Poon (2003) analyse empirical time-series cross-Sectional data from 265 firms located in 15 countries, using S&P ratings, over 1998-2000 and find that unsolicited ratings were significantly lower than corresponding solicited ratings. However, they also find that companies that chose not to obtain a rating from S&P typically had weaker financial profiles, a potential cause for the decrease in rating. Poon (2003) shows that the difference in ratings was explained by the significant self-selection bias,[13] but looking at a Japanese sub-sample it is found that unsolicited ratings were still lower than solicited ratings even after they had controlled for differences in sovereign risk and financial factors, suggesting that there are significant affects that should be accounted for. Poon and Firth (2005) then build on the previous paper and examine a pool of 1,060 bank ratings using a two-step treatment effects model.[14] They find similar results; that unsolicited bank ratings were lower, but again this was partly explained as banks with unsolicited ratings tended to be smaller and have weaker financial profiles.

There have been other studies that show that unsolicited ratings are lower. Van Roy (2013), looking at banks rated by Fitch and S&P, also shows that unsolicited ratings tend to be worse (after accounting for differences in observable bank characteristics). However, Van Roy (2013) attributes this to the fact that the ratings are based on only publicly available information and hence therefore dependent upon the quantity of information disclosed by banks and not to self-

[13] Bongaerts et al. (2012) also find self-selection bias and describe it as the adverse selection, where firms that obtain favourable unsolicited rating do not apply for a solicited rating and firm that receive a poor unsolicited rating pay for a solicited opinion. They state that this may explain why unsolicited ratings are typically lower than solicited ones.

[14] This a combination of the treatment effects model and Heckman's two step estimation method.

selection bias. Van Roy (2013) reveals that the result is consistent with CRAs "blackmailing" low-disclosure firms, but state that "blackmailing", if used, is not an effective method at making the firms pay for ratings.

Bannier et al. (2010) also cite self-selection bias as a potential cause of the difference between solicited and unsolicited ratings. They examine why unsolicited ratings tend to be lower in a sample of default indices of non-US borrowers in 1996-2006 and conclude that both self-selection on the side of the issuers and strategic conservatism on the side of the CRA play a part. This conservative bias arises as CRAs are more likely to incur scrutiny or penalties from positively biased ratings rather than negatively biased ratings. Bannier et al. (2010) also observe that this downward (conservative) bias increases with a bank's opacity.[15]

Byoun et al. (2014) find a different result. Using firm performance, based on long run stock performance, they find that new unsolicited ratings are followed by negative performance and that no significant long run performance change follows solicited ratings. Byoun et al.'s (2014) results are counter to the conservatism hypothesis (downward biased). Byoun et al. (2014) also show that firms with solicited changes have a corresponding abnormal stock performance, while unsolicited changes result in zero abnormal stock performance. This is expected as solicited ratings are based on additional information (and when it enters the market it impacts the stock price), whereas unsolicited are based on publicly available information. Jorion et al, (2005) and Henry et al. (2015) argue that if CRAs enjoy an increased informational advantage this will stimulate large stock price reactions to rating changes.

In general, the literature has shown that unsolicited ratings are lower (see Table 2.3), although there are mixed findings on the impact of unsolicited ratings on rating informativeness.

2.2.3 COMPETITION AND REPUTATION

The credit rating industry in most of the world is an oligopoly, for instance in the EU in 2017 the biggest three CRAs (Moody's, S&P and Fitch) held 93.18% of the total market share (ESMA, 2017b) and in the US the same three CRAs rate 96.4% of all outstanding rating that were issued by SEC certified CRAs (SEC, 2017).[16] This is in part due to the extremely high

[15] Presumably, because the uncertainty over the rating increases.

[16] The big three CRA companies, in the US, also provide the ratings for; 87.8% of financial institutions, 60.7% of insurance companies, 89.2% of corporate issuers, 87.5% of asset-backed securities and 99.1% of government securities (SEC, 2017).

barriers to new entrants (Coffee, 2011), which is in turn down to the nature of the credit rating industry. For a CRA to obtain work and clients, they rely on their reputation and track record of accurate and reliable ratings. However, new CRAs would naturally lack such a track record and as such it is difficult to break into the market and obtain new clients. Even CRAs with an excellent track record could find it difficult to make investors aware. Bai (2010) identifies the importance of the 2006 CRA reform act's (US) requirement that CRAs disclose statistics for measuring the accuracy of their rating actions[17], which aids issuers and investors in evaluating CRAs.

There are many factors that can affect the benefits of building a CRAs reputation. In Klein and Leffler's (1981) model, the benefit of building reputation is affected significantly by competition, predominantly negatively. Klein and Leffler (1981) argue that competition reduces the impact of reputation in two ways; (i) reputation is valuable as it may increase the value of future sales/issues and competition typically decreases the amount charged for services, (ii) demand elasticity increases in a competitive market, increasing the need to decrease prices or find an alternative way to win business. Both these factors act to undermine the value of maintaining the CRA's reputation as a means of increasing future revenue.

Counter to this argument, Horner (2002) argue that only when consumers (issuers) have a choice of CRA, a loss of reputation transmutes into a loss of business. In this scenario competition is a critical factor in enforcing the need to maintain one's reputation with respect to the other CRAs. These two positions are not mutually exclusive and the argument whether competition between CRAs has a positive impact on the quality of their ratings has been a hot topic over the past few years (Bolton et al., 2012; Becker and Milbourn, 2011; Dittrich, 2007).

Bolton et al. (2012) investigate conflicts inherent in the reputational model. They focus on three sources of conflicts: (i) understating risk to attract business, (ii) ability of an issuer to purchase only the most favourable ratings and (iii) trusting nature of a proportion of investors. Using their model, they observe that competition reduces efficiency, due to rating shopping, and that ratings have an increased chance of being inflated in good economic times as investors are less cautious.

To test the effect of increased competition in the market, Becker and Milbourn (2011) empirically evaluate the entry of Fitch into the credit rating market. They use corporate bond ratings from 1995 to 2006 and find that the increased competition provided by Fitch

[17] These include the default rates of each rating category.

corresponds to a decrease in ratings quality. The decrease in ratings quality occurs in three ways: (i) rating levels went up, (ii) correlation between market implied yields and ratings decreased and (iii) ratings ability to predict default decreased. This supports the original argument put forth by Klein and Leffler (1981) that increased competition can work counter to reputation and decrease the quality of ratings.

Recent changes in regulatory framework in both the US and EU (see Section 2.3) have acted to increase competition in the CRA market. But as of writing the "jury is still out" on whether a more competitive CRA market can improve ratings quality (see Table 2.4) and as such the changes will provide a unique opportunity to study and further the arguments for or against competition of CRAs.

2.2.4 RATINGS SHOPPING AND ITS LINK TO COMPETITION

On obtaining their rating, an issuer may choose whether they wish the rating to be publicly published (depending on whether it is favourable enough). The presence of this feature combined with multiple CRAs, means that an issuer could "shop" for the most favourable ratings. This scenario is modelled by Faure-Grimaud et al. (2009), showing that clients would only hide their ratings under certain conditions: (i) they are sufficiently uncertain of the ratings quality when obtaining a "certification intermediary" and (ii) their decision to purchase a rating was not observable. It follows logically that to purchase a rating and not reveal it would send a clear signal that the rating was not of satisfactory quality. Both Bolton et al. (2012) and Faure-Grimaud et al. (2009) conclude that competition between CRAs can reduce efficiency. As it can lead to less information being revealed in this equilibrium, as the more CRAs the greater the chance, or availability, of rating shopping. Skreta and Veldkamp (2009) and Sangiorgi and Spatt (2016) also demonstrate how rating shopping con occur in a market with trusting investors.

2.2.5 CONSCIOUS AND UNCONSCIOUS BIAS IN CRA DECISION MAKING

A CRAs rating is the expression of an *opinion*[18] about the probability of default (risk), these opinions are the work of complex analysis, assumptions and judgements. Bias (either conscious or unconscious) can creep into the judgement phase (Boylan, 2012). It is vital that regulators,

[18] It is both quantitative and qualitative.

academics and others distinguish between *conscious* and *unconscious* bias as they must be dealt with differently. Regulation or policies aimed at reducing bias will be more effective at reducing once type than the other. For instance, a fine or other penalty for providing inaccurate information would be effective at mitigating *conscious bias*, but be relatively ineffective at reducing *unconscious bias*, as the CRA analyst may truly believe they were providing accurate information.

The source of unconscious bias can be put down, in part, to the vast quantity of complex information that goes into making such intricate decisions. Boylan (2008) shows that people's opinions are shaped by their own self-interests through a study which asked pairs of subjects (assigned roles of a manager plus an auditor) to accurately estimate the value of an item (its value would depend on the number of objects in a container). The auditor was financially incentivised to provide accurate valuation, whereas the manager was incentivised to provide higher (overstated) or lower (understated) valuations. Boylan (2008) finds that auditors matched with managers, who were incentivised to overstate the value of the item, were led to believe that the item was more valuable (even though this was directly against the auditor's financial incentives). Similarly, Bazerman et al. (2002), with professional accountants, also find evidence of unconscious bias.

Boylan (2012) reports that three of the most significant sources of unconscious bias are:

- ***Availability*** – Tversky and Kahneman (1973) and Tversky and Kahneman (1974) state that easily available information has a "disproportionately" strong influence on an individual's judgement. CRAs have limited sources of information on which to base their ratings, the main source of information is the issuer, with whom they work closely. The issuer is clearly incentivised to obtain high ratings and as such may provide information and evidence that is biased in favour of a positive outcome. Boylan (2012) notes that there is "no external party providing an effective counter weight in the process".
- ***Representativeness*** – Tversky and Kahneman (1974) and Kahneman and Tversky (1982) state that positive past performance usually causes excessively optimistic projections of future performance. The lead up to the sub-prime mortgage crisis is a clear example of this, as companies and CRAs assumed continuation of the past rising trend.
- ***Anchoring*** – Tversky and Kahneman (1974) state that people tend to overvalue initial information relative to incremental information when making judgements. Anchoring

can be seen prior to the sub-prime mortgage crisis where CRAs held firm to the high ratings they had placed on mortgage back securities in the face of increasing mortgage defaults that were much large than expected.

The role of unconscious bias has had only small coverage in academic literature and warrants further investigation as it may play a significant role in the accuracy of credit ratings.

2.2.6 LACK OF TRANSPARENCY

Promoting CRA transparency has been the aim of regulators long before the recent financial crisis (Hunt, 2009). Two distinct kinds of transparency are considered: (i) methodological transparency, the ability of an outsider to understand how the CRA arrived at the rating produced and (ii) performance transparency, the ability to distinguish how well the ratings perform after they have been awarded.

Both are necessary for an observer to assess the accuracy of a CRA ratings. Many studies (Sy, 2009; Bolton et al., 2012) have stressed the importance of opening the so called "black box" of rating methodology, thereby enabling investors to make an informed judgement about the risks involved with investing in a rated security. With regulators (see Section 2.3) aiming to increase the competition in the CRA market, it is vital that there is adequate performance transparency, so issuers and investors can make an informed judgement about the quality (accuracy) of a CRAs historical ratings and rating performance.[19]

2.2.7 LACK OF LIABILITY

Legal liability, which enables investors and issuers to claim recompense if they can prove that they have lost out due to a CRAs negligence or bias, is known to have both positive and negative effects on rating quality (Goel and Thakor, 2011). Prior to the regulatory changes there was little recourse for investors and issuers and CRAs were not liable for their ratings.

Goel and Thakor (2011) develop a theoretical model which examines the impact of increased regulation and liability and predicts three things. Firstly, that increased legal penalties levied because of incorrect ratings can induce CRAs to increase the effort put into ensuring that the

[19] i.e. for investors and issuers to be able to gauge the accuracy of a CRA ratings, there must be enough easily accessible and comparable information to be able to make the judgement.

ratings are accurate, while leaving the number of ratings produced unchanged. Secondly, that increased legal liability may reduce moral hazards. Lastly, it can cause a downward bias in ratings, as CRAs seek to protect themselves from the increased scrutiny. Lower ratings are less likely to incur scrutiny than higher ratings (Bannier et al., 2010). Both the US and EU regulatory changes contain increased legal liability initiatives to tackle CRAs.[20] The EU has successfully levied three fines against CRAs under the new regulatory regime: They fined Moody's UK and Moody's Germany €1.2 million in 2017 for failing to publicly disclose the methodologies it used to determine certain ratings decisions on EU institutions. They fined Fitch €1.38 million in July 2016 for a series of negligent breaches. While the US is yet to levy a fine (under the new laws) against CRAs, in 2015 they did fine S&P $1.5b for their role in the financial crisis, but this was not for breaches of the new regulation.

2.2.8 PROBLEMS WITH RATING METHODOLOGY

Many of the criticisms surrounding rating methodology are grouped into two area, (i) the methodology is too opaque and (ii) the methodology is outdated or inadequate. In 2015 ESMA conducted a review of CRA methodologies (ESMA, 2015a). The document draws on the supervisory experience of the ESMA in 2014 and 2015 and reveals a number of interesting findings (see Table 2.5). For instance (i) in cases where there is limited quantitative evidence, the CRA will typically use qualitative measures to show that the methodologies were appropriate predictors of credit worthiness (ESMA, 2015a, point 27), (ii) CRAs were unable to perform tests to confirm the discriminatory power of their methodologies (even where ESMA considered there to be sufficient evidence to do so) and (iii) the validation techniques used to demonstrate the discriminatory power varied between CRAs. ESMA (2015a) state that they believe that "CRAs should enhance the validation techniques they apply in such cases and put in place more qualitative measures in order to perform a more robust validation" that is based on their historical experience with their methodologies. As a follow up to this report, in 2017 ESMA published guidelines on the validation and review of CRAs methodologies (ESMA, 2017a). The report clarifies ESMA's expectations on the measures CRAs should use and provides examples of complimentary measures they should consider employing.

[20] The US in the Dodd-Frank act Section 933. The EU published a 2013 directive, Regulation (EU) No 462/2013 of the European parliament and of the council article 35a.

2.2.8.1 Sovereign rating methodology

Recent criticism of the way CRAs handled sovereign ratings in the European sovereign debt crisis has brought the issue of sovereign rating methodology to the fore. Eijffinger (2012) assesses the documents on rating methodology published by the CRAs, they find that they differ in length clarity and quantitative content.[21] Eijffinger (2012) states that CRAs are transparent about which indicators they use and where they obtain their data (Eijffinger (2012) praises S&P in particular for providing a thorough overview). However, they only explain qualitatively how the indicators are applied, not quantitatively. Eijffinger (2012) explains that what is missing is an explanation of how the aforementioned indicators are weighted and as such it is difficult to judge how much of a role each one plays when it comes to impacting the rating. With the recent regulatory changes and disclosure requirements for CRAs it would be beneficial if an updated study could be done to: (i) assess if the CRAs have been induced to disclose more information about their methodology and (ii) assess if the sovereign rating methodology has changed post regulatory reform.

Several studies have tried to determine the indicators and their corresponding weights (Mellios and Paget-Blanc, 2006; Hill et al., 2010; Afonso et al., 2011). While the determinants are known, the weights are not easily inferred, making it difficult to reverse engineer a CRAs decision process. Other problems arise such as the interlinkage of sovereign ratings, CRAs attempt to smooth their rating changes using the "through the cycle" (TTC) method,[22] this however has drawbacks and can lead to what Eijffinger (2012) calls "cliff effects".[23]

The ESMA undertook a thematic investigation into the sovereign rating process by CRAs in the summer of 2013,[24] where over 60 interviews were conducted at the three largest CRAs. The

---

[21] They assess a document from each:
Fitch (2011), Sovereign Rating Methodology, Available at
www.fitchratings.com/creditdesk/reports/report_frame.cfm?rpt_id=648978
Moody's (2008), Sovereign Bond Ratings, Available at:
www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_109490
S&P (2011), Sovereign Government Rating Methodology and Assumptions, Available at:
http://img.en25.com/Web/StandardandPoors/CriteriaGovernmentsSovereignsSovereignGovernmentRatingMethodologyAndAssumptions_1365.pdf

[22] There is a contrasting point in time (PIT) rating which concentrates on the present condition of the issuer and ignores the state of the business cycle (Eijffinger, 2012).

[23] Eijffinger (2012) explains that cliff effects are when the rating changes less frequently, but when it does change it is likely to push the bond below investment grade, which then in turn causes market participants to liquidate it. The TTC method smooths ratings so a recession (or boom) does not lead to a corresponding downgrade (or upgrade), however when the recession is due to a crisis (i.e. not cyclical changes) then the rating may need to be sharply adjusted down, hence giving a "cliff effect".

[24] ESMA has issued several investigations: (i) 2013 – sovereign rating process, (ii) 2014 - structured finance ratings, (iii) 2016 – governance, strategy and fees and (iv) 2017 – thematic review of validation and endorsement guidelines for CRAs.

aim was to assess "governance, conflicts of interests, resourcing adequacy and confidentiality controls associated with the sovereign rating process" (ESMA, 2014).

The investigation identified failings in several areas. With regards to conflict of interest and independence the ESMA identified potential risks and actual failures that could potentially lead to issues with the quality of ratings and a loss of independence in the ratings process. These include (ESMA, 2013)[25]: (i) senior management becoming involved with the sovereign rating process, (ii) involvement in the sovereign rating process by the independent review function, (iii) involvement by non-rating teams in rating activities and (iv) problems with how the appeals procedure worked in practice.

The ESMA also highlighted deficiencies found in how confidential rating information was managed, which include: (i) disclosure of upcoming rating actions to an authorised third party, (ii) inadequate controls regulating the circulation of rating information within the CRA, (iii) use of external communication consultants and (iv) inappropriate controls and permissions for accessing ratings information.

2.2.8.2 Bank rating methodology

There are several unique features of the banking sector that make it difficult to gauge risk. These include the opacity of the industry (Flannery et al., 2013; Iannotta, 2006; Morgan, 2002), the complex nature of business conducted and the financial instruments (e.g. RMB, CDO etc) held by such institutions. Additionally, the degree of external help that the bank may receive if it is in financial trouble is uncertain. Packer and Tarashev (2011) argue that the level of external support, systemic risk and volatility of bank performance must all be taken account when gauging a bank's risk. External support can play such a strong role that CRA often issue two ratings for a bank, a *stand-alone* rating and a rating that also takes account of any external support.

Investigations into the determinants of bank rating quality (Hau et al., 2013) conclude that: (i) bank ratings are counter cyclical,[26] (ii) the ratings bias is in favour of large banks and is economically significant, (iii) a traditional banking model with a large loan share increases the credit rating accuracy, this is most likely as is reduces the complexity of the rating, (iv) they

[25] A further problem was (ESMA, 2014b), revenue generating research publication activities carried out by CRAs.
[26] They state that in "normal" times bank ratings are only informative for the lowest 25% of ratings (BBB+ and below), and they show that banks with AAA and A are equally likely to become distressed.

find that CRA give systematically better ratings to those banks that provide a large quantity of rating (of asset backed securities) business. Other variables that are used to explain bank ratings include ROA, LLR, ETA, LTA and LNASSET and SOV (Poon et al., 2009).[27] An additional factor that makes banks more difficult is the feature that a bank's earnings performance is highly volatile.

It is not only firm specific factors that must be taken into account. Packer and Tarashev (2011) highlight the importance of correctly assessing not only the bank's risk, but also the "vulnerabilities that may build up in different parts of the financial system, as well as on interlinkages in this system". Because of this, a banks rating should reflect the financial, industrial and economic environment of its business.

2.2.8.3 Structured finance rating methodology

Rating structured financial products experiences many of the same problems as mentioned for sovereign ratings, i.e. TTC, "cliff effects" and sluggish changes[28]. The issuer pays model and associated problems play a much stronger role in the structured finance rating industry (Eijffinger, 2012).

Partnoy (2006) discusses in depth the problems inherent in rating methodologies and his work focusses on rating structured finance and collateralized debt obligations (CDOs). CRAs are involved with the rating of CDOs (Tavakoli, 2004), of which there are two types, Cash flow CDOs[29] and Synthetic CDOs[30]. Both of these enable arbitrage opportunities and as such are created with this motivation in mind. Partnoy (2006) states that CRA developed methodologies for rating CDOs which resulted in the various combinations of bands (or tranches) being worth a greater amount than the underlying asset. This difference in price is sizable as it covers the fees the CRAs and other players charge for structuring and arranging the CDO and managing the underlying assets. How can the CDOs be priced higher? There are two theories, first that the creation of the CDO adds value as it i) allows players in the market, who would not be able

[27] The variables being: ROA = Return on assets, LLR = Loan loss ratio, ETA = Equity to assets ratio, LTA = Loans to assets ratio, LNASSET = Log of assets and SOV = sovereign rating.
[28] CRAs took a long time to recognise losses from sub-prime financial instruments (Eijffinger, 2012; White, 2010).
[29] They involve the purchase of fixed-income assets, the cash flows of which are used to remunerate investors in the various band (or tranches) (Partnoy, 2006).
[30] Synthetic CDOs use credit risk exposure but without the underlying assets, it is achieved by selling protection on the underlying assets using CDSs (Partnoy, 2006).

to invest in the types of portfolios underling a CDO, to then invest in them and ii) the underlying assets were incorrectly priced. Partnoy (2006) thinks this first theory is unlikely.

The second theory hinges upon CRAs methodology being so complex, subjective and unknown that opportunities for market participants to create ratings *arbitrage opportunities*, without adding any tangible value, are made. This ability of market participants to manipulate the inputs, and hence creating products with increased value, is a clear problem of CRA methodology and shows that they perhaps work too closely with investment firms, especially as many CRAs offer advisory services where issuers are schooled on how best to structure such assets. There are other potential reasons for the increase in value; errors in rating the assets, errors in correlation between the assets and the tranche pay-outs (appearing to give a higher pay-out and hence higher rating) or errors in the rating the CDOs individual tranches (Partnoy, 2006).

During the 1990s and early 2000s S&P and Moody's worked closely with investment banks to create models for rating financial products (e.g. CDOs). One such model is S&P's CDO Evaluator, which uses Monte Carlo simulations to predict the loss distribution and time to default of assets in a CDO's portfolio. The level of defaults would be based on the ratings of the underlying assets and it also accounts for proportion of the asset which could be recovered after default. They aim to determine what proportion of the time a "loss trigger" is breached, for instance to obtain a AAA rating, the product (CDO) may need to withstand a 30% default rate in the asset pool for a set amount of time. The most junior tranches absorb the losses first up to a certain point and then the next most junior would absorb the losses up till the following level. Each of the tranches (or levels) will then be assigned a rating based on their performance in the simulation. However, these are based on assumption of important variables, such as expected default rates, correlation between assets and recovery rates (Partnoy, 2006).

With all simulations (or models) rating methodology is limited to *rubbish in, rubbish out*.[31] Some limiting factor that have been identified in such models include: (i) various assumptions made, (ii) asset correlation not being correctly accounted for, (iii) not accounting for various sources of variation (e.g. geographical) and (iv) allowing asset managers to use CRA assumptions rather than the market assumptions, hence creating an arbitrage opportunity. All of this leads to a false level of mathematical precision which may be incapable of reflecting the actual risk.

[31] i.e. if the underlying assumptions are poor, then the resulting model will also be.

Consequently, investment banks were too heavy involved in rating financial products (typically CDOs), they would even run the models and performed many of the complex calculations on behalf of the CRA. S&P (2002) are quoted as stating that the "transactions sponsor or banker will generally perform the cash flow modelling and provide Standard and Poor's with the results and the model". To quote Partnoy (2006) "The process of rating CDOs becomes a mathematical game that smart bankers know that they can win".

2.2.9 THE REGULATORY LICENCE VIEW OF CREDIT RATINGS

The regulatory licence view is that ratings are valuable not because of the information they convey on the credit quality of issuers and securities, but because they are important in reducing costs related with regulation (Partnoy, 1999). Regulators have been attempting to reduce regulatory dependence in the recent regulatory changes by reducing reference to them in regulation and by attempting to mitigate the mechanistic market reaction to rating downgrades.

This is refuted by Bedendo et al. (2018), who evaluate the impact of reputational shocks on the informational content of credit ratings. They examine stock price responses to downgrades and upgrades of US corporate issuer ratings in the two years pre and post episode of reputational distress.[32] They find that stock price responses to rating downgrades strengthen significantly in the periods following a reputational shock, i.e. credit ratings become more informative when CRAs are at risk of losing their reputation (market reactions contain a reputational component). The presence of a reputational component supports the information intermediary view,[33] as it is indicative of investors attaching a greater informational value to ratings than simply their regulatory content.[34]

2.2.10 THE STRUCTURED FINANCE CRISIS

In the early 2000s, CRAs took an important role in securitizing US residential mortgages and the marketing of financial products that were based in part on those mortgages (Boylan, 2012;

[32] The three crisis periods used are the Enron/WorldCom failure in 2001-02, the subprime crisis in 2007-08 and the S&P lawsuit filed by the US government in 2013.
[33] That the main role of CRAs is to act as information intermediaries, by reducing the information asymmetry between issuers and investors, and providing investors with reliable signals concerning the credit quality of issuers (Bedendo et al., 2018).
[34] Which is what the regulatory licence view argues.

Hunt, 2009). There is little doubt that CRAs played a significant role in exacerbating the crisis (Coffee, 2011).

Investment banks purchased residential mortgages in bulk from commercial banks and mortgage companies and repackaged them in the form of bonds to sell to investors. This would, they argued, diversify the risks as pooled mortgages were from a wide variety of different geographic areas and as such an investor would only end up suffering small losses, compared to if they held a single mortgage or a single geographic region. Investment banks then assigned the cash flows from the underlying mortgages to different residential mortgage backed securities (RMBS), thereby constructing various bonds with differing levels of credit risk. The bonds with the lowest risk would have the first rights to receiving payments from the underlying mortgages and therefore offer the lowest return, riskier bonds with lower priority would then offer higher returns.

CRAs were then hired to evaluate the bonds and assign a rating. However, the investment banks were keen to obtain high ratings as one of the most significant demands for such bonds came from institutional investors (e.g. pension funds) and they were only allowed to purchase the safest financial products (e.g. investment grade) (Bethel et al., 2008). The bank would structure the RMBS in a way that resulted in them receiving the coveted AAA rating. The CRAs would then analyse the structure of the security and the underlying cash flows and enter the data into their propriety quantitative models to arrive at a rating. If the investment bank was unhappy with the arrived upon rating (not AAA), they were given an opportunity by the CRAs to modify the contents in a way that would help it achieve the desired rating. This process, of modification by the investment bank and assessment by the CRA, would then continue until the bank was happy with the outcome.

Bonds that did not meet the risk level were then chopped up and repackaged into collateralized debt obligations (CDOs), where RMBS are the underlying assets, of which many perversely also received the sort after AAA rating. Although pioneered in 1980s (Hayre, 2002) the market for RMBS grew rapidly in the early 2000s (Ashcraft and Schuermann, 2008) and with it the demand for CRA to rate them.

The CRAs would continue to monitor the RMBS and CROs and would in the event of negative news (many defaults in a certain area) downgrade or review the rating. However, in the time prior to 2007, in which it is now known there were many mortgage defaults, the majority of these financial securities held onto their AAA ratings. Then in mid-2007, many contributing factors (including falling house prices, defaults and fraud) forced the CRAs downgrade vast numbers of these RMBS and CDOs. This caused a mini perfect storm, as (i) institutional investors who had purchased large amounts of these products were forced to sell them (as it was against their policies to hold such risky investments), (ii) falling house prices and (iii) the market for such bonds began to evaporate. Any organisation holding such bonds incurred vast losses; this included many of the original investment firms who had held onto part of the securities. Hunt (2009) estimates that by July 2008 36% of all CDOs based on US asset backed securities had defaulted.

It is concluded that CRAs did a bad job of assessing the risk of default of CDOs and RMBS post 2003 (Financial Stability Forum, 2008) and that these highly rated securities had an unwarranted effect on valuation and liquidity of RMBS and CDOs (IOSCO, 2008). In early 2015, the US justice department secured a $1.375 billion settlement with S&P for defrauding investors in the lead up to the financial crisis.[35]

2.2.11 THE EU SOVEREIGN DEBT CRISIS

CRAs came under fire not only for the 2008 financial crisis, but also for their role in the European sovereign debt crisis. The IMF (2010) state that the most pressing risk at the time facing global economies was that of sovereign default (IMF, 2010).

After the 2008 financial crisis, a number of European country's sovereign bond yield spreads increased substantially (greater than expected by typical factors, e.g. inflation, economic growth) (Afonso et al., 2012). Afonso et al. (2012) state that increased bond yields are down to the increased awareness by markets to different macro and fiscal fundamentals (significantly fiscal imbalances).

Consequently, there were several sovereign rating downgrades which only acted to increase the rise of sovereign bond spreads. Sovereign ratings act as a "ceiling" for any ratings assigned to non-sovereign issuers in the country (Alsakka and ap Gwilym, 2013). Hence, as several countries were downgraded (Greece, Ireland and Portugal) so too were the banks and financial institutions within the countries (in fact some fell to ***speculative*** ratings).

[35] The Department of Justice issued a statement in 2015, "Justice Department and State Partners Secure $1.375 Billion Settlement with S&P for Defrauding Investors in the Lead Up to the Financial Crisis", available at: https://www.justice.gov/opa/pr/justice-department-and-state-partners-secure-1375-billion-settlement-sp-defrauding-investors

Sovereign credit ratings play an important role in the working of the sovereign debt market and as such they effect the sovereign's cost of borrowing. It follows then, that the lower the sovereign was downgraded (e.g. Greece) the costlier it was for them to borrow, which exacerbated the crisis.[36] Just as in the sub-prime crisis, with structured financial products, a sluggishness in CRAs reactions was observed with respect to sovereign ratings in the recent European sovereign debt crisis (Eijffinger, 2012). Afonso et al. (2012) examine how markets reacted to sovereign rating announcements and find that markets chiefly react to negative announcements and observe the presence of spill over effects in EMU countries from lower rated to higher rated countries, adding to the spread of the crisis.[37]

It is well established that the sovereign rating of a country acts as a "ceiling" for the rating of financial institutions (Almeida et al., 2017; Klusak et al., 2017; Huang and Shen, 2015; Hill et al., 2010). A fall in a sovereign rating can impact the rating of many of banks in the country. Hence, changes in sovereign risk can be transferred to the banking sector through the sovereign-bank ratings channel (Alsakka et al., 2014). A fall in bank ratings can impact bank behaviour and potentially worse the economic situation. This emphasises the importance of accurate and timely sovereign ratings as they can have wide ranging implication.

Because of the role of CRAs in the crisis the European Commission (EC) set out to identify the main deficient areas of CRAs. They conclude that there was (EC, 2014; Alsakka et al., 2015): (i) failures in integrity, conflict of interest with issuer pays model, (ii) failures in reliability, over reliance on their ratings by market participants and regulation and (iii) a lack of transparency, inhibiting investors ability to understand how agencies arrive at their rating and the ability to monitor how those ratings are performed (Hunt, 2009).

2.2.12 CONCLUSION

There has been much criticism of the CRA industry. It has centred around three key areas; (i) problems with the issuer pays model and inherent conflicts of interest, bias and ratings solicitation, (ii) issues with CRA methodology, transparency and legal liability and (iii) competition in the industry.

Many academics have criticised the issuer pays business model, but with limited viable alternatives that would require a substantial system overhaul it is unclear whether any

[36] Greek 10 year bond yields rose to approximately 37%.
[37] They showed that rating announcements are not anticipated at the 1-2 months horizon.

significant change will be made to the current market. The academic community is still divided as to whether increased competition would have a positive effect, however (as seen in Section 2.3) politicians have clearly decided that action is better than inaction and have instituted new regulations to increase competition. As to whether this is the correct course of action or will be implemented effectively is yet to be seen.

The structured finance crisis caused CRAs to face numerous criticisms that again centred on methodological issues (working too closely with financial institutions), conflicts of interest inherent in the business model and a reluctance to update ratings on products that were clearly overvalued. These failings were concluded to have a significant impact and effect that did contribute to the financial crisis.

In the European Sovereign debt crisis, the timing of rating changes was once again condemned and blamed for potentially exacerbating the crisis. The sudden and sometimes severe downgrading of sovereigns lead to a transmission of risk into the banking sector through the sovereign-bank rating channel. This clear failure of CRAs not just in Europe but also on the world stage has raised vital questions for regulators, academics and the industry on the best way to adapt the industry to promote more accurate and timely ratings. In the following Section (2.3) a brief background on historic CRA regulation in the EU and US will be provided.

2.3 CRA REGULATION

2.3.1 REGULATION BEFORE 2008

In the European Union (EU) before 2010, there was no legislation directly addressing CRAs (Alsakka et al., 2015). There existed a form of self-regulation that followed the IOSCO (or International Organization of Securities Commissions) Code. However, this was not enforced and was only applied voluntarily (Johnson, 2004). It was argued that additional regulation was not needed as CRAs depend heavily on their reputation (Möllers and Niedorf, 2014). Also, there were worries that any authorization procedure would result in EU governments becoming liable, to some extent, for the published ratings and also cause a certain amount of market isolation (Möllers and Niedorf, 2014).

The recent regulatory efforts involving CRAs can be traced back to the US sub-prime debt crisis (where CRAs played a significant role as they were deeply involved in rating structured financial products (such as mortgage bonds etc) (Alsakka et al., 2015), and to the EU sovereign debt crisis. The role CRAs played in these two crises brought CRAs into the political and public spotlight, as it highlighted their role in financial and economic stability (Alcubilla and Del Pozo, 2012).[38]

The US historically has had a very different approach to CRAs compared to the EU, as it has had authorization procedures for CRAs since 1975 (Hunt, 2009; Behr et al., 2018). This early regulation enacted new capital requirements that were based specifically on ratings. The competitive environment for CRAs was also irrevocably changed when the SEC decreed that only ratings from certain CRAs could be used in the regulations (Moody's, Fitch, S&P) (Behr et al., 2018). This introduced the concept of the Nationally Recognised Statistical Rating Organisation (NRSRO). While the actions dramatically increased the significance of CRAs, it limited competition by raising barriers to entry. Behr et al. (2018) find that this regulation enacted in 1975 led to rating inflation.

In the early 2000s, a new wave of regulatory reform was triggered as CRAs were thrust into the spot light after the Enron scandal. CRAs issued investment grade ratings mere days before the firm declared bankruptcy (Smith and Emshwiller, 2001), this naturally brought into question the accuracy and thoroughness of their ratings. As a result, the Sarbanes-Oxley Act

[38] See Sections 2.2.10 and 2.2.11.

of 2002 instructed the SEC to investigate CRA performance, having done this the SEC issued a report in 2003 regarding the role and function of CRAs (SEC, 2003). After examining the report and further investigation Congress enacted the 2006 Credit Agency Reform Act[39].

The 2006 act handed regulatory authority over CRAs to the SEC. However, it also limited the SEC's jurisdiction in a number of substantial ways (Hunt, 2009), e.g. the SEC couldn't regulate the substance of the credit ratings or the methodologies used and it gave no private right of action. The act and subsequent rules were adopted by the SEC in June 2007. With two of the main aims of the 2006 act being to make improvements in transparency, both in the respect of methodological and performance. However, the larger CRAs put rather unspecific descriptions of their procedures and as such, not much was added to what was known of the methodology.[40] Additionally annual performance reports were required, but these were already being issued by CRAs and the SEC did not specify a standardized format. It was therefore unclear how much these new rules have impacted the ratings.

It is clear that prior to the recent crises there were two different approaches being applied; (i) that of Europe's distinct lack of regulation and (ii) the US attempt to put in place a stronger regulatory regime due to some recent financial scandals (Enron). After the 2008 financial crisis, both the US and Europe moved to increase regulatory stringency.

2.3.2 EU REGULATION

Following the 2008 global financial crisis, the introduction of new regulation to tackle CRAs was split into three phases: the reactive phase, the implementation phase and the enhancement phase.

The reactive phase involved regulators and policy makers debating and outlining (in a series of meetings from October 2007 to October 2010) a new set of laws aimed at tackling the CRA industry. Much of the debates centred around new registration procedures for CRAs, rules to reduce conflicts of interests and the sanctions that could be imposed.

The implementation phase was composed of two parts. Firstly, in September 2009 the European commission (EC) enacted the first new piece of regulation, CRA I. This initial wave of regulation sought to address conflicts of interest in the rating process through comprehensive

[39] Credit Rating Agency Reform Act of 2006, 120 Stat. 1327, codified at 15 U.S.C. § 78o-7.
[40] This is due to the SEC only requiring the CRAs to "explain" their procedures instead to the actual procedures and methodologies themselves (Hunt, 2009, p23).

disclosures by CRAs of their rating methodologies, historical performance and annual transparency reports (see Table 2.6). Additionally, new powers and penalties for regulators and member states were outlined. However, the regulation was not properly enforced until July 2011 (CRA II) when the EC established the newly created European Securities and Markets Authority (ESMA) and charged them with overseeing the regulation. ESMA was also tasked with mitigating the mechanistic reliance on credit ratings and to reduce the potential for market overreactions to rating actions (Alsakka et al., 2015; Alsakka et al., 2017; EC, 2014).

Finally came the enhancement phase, where refinement of and improvements to the regulation were made. This came in the form of CRA III enacted in May 2013, which made updated many of the existing rules. Most significant of these changes was the instigation of a new civil liability regime and expansion to the transparency and monitoring requirements. The new civil liability regime means that issuers and investors would be able to sue a CRA if they had lost out because of a rating and prove that the CRA was culpable of misconduct or negligence (OJEU, 2012). New rules governing the establishment, maintenance and enforcement of effective internal control structures governing the implementation of policies and procedures to prevent and mitigate possible conflicts of interest were introduced alongside further methodological and performance transparency rules.[41] CRA III strengthened the existing rules and made Europe one of the most regulatory stringent markets for CRAs to operate in.

The final phase (CRA III) also brought in some changes specifically designed to change the way CRAs rate sovereigns because of their role in the EU sovereign debt crisis. These include insuring the market has enough time to absorb new rating announcements to prevent market over reactions and providing the underlying facts and assumptions that the ratings are based on, to promote understanding of the ratings and how they are formulated. This should enable market participants to look at the ratings more objectively and reduce their reliance on them.

ESMA did undertake a thematic review into bank rating methodology in 2012 and 2013.[42] A subsequent report published in March 2013 detailed the remedial action plan for each CRA, which include (i) developing more rigorous internal procedures and policies to better adhere to the requirements, (ii) establish new processes to ensure the quality of the information to be used when ratings are issued and monitored, (iii) standardised and codified guidance, analytical

[41] The EU also implemented a mandatory 4-year rotation policy for structured finance ratings to help boost competition and prevent clients and CRAs working to closely.
They also implemented measures limiting shareholding and voting rights in CRAs.
[42] Much of the more specific aspects of the regulation is aimed at tackling either structured finance or sovereign ratings.

criteria and instruments that comprise the existing practises (for rating banks) and also disclosing these to the ESMA and the public,[43] (iv) updated methodologies to include details of qualitative and quantitative factors that are used in the methodology,[44] (v) improved general access for the public to their rating methodologies, enhance internal peer review practices and improved record keeping and review mechanisms (for the technical details for models and analytical tools).

What is most notable in the EU, is the dramatic shift from a region with an almost non-existent regulatory regime, to what is perhaps the world's most stringent CRA regulatory regime. This provides regulators and the academic community with an excellent chance to study the impact of such a dramatic shift in approach. Notable changes include: the introduction of a civil liability regime, tougher disclosure, methodological and transparency requirements for CRAs and the introduction of a new regulatory body (the ESMA).

2.3.3 US REGULATION

In the US, as in the EU, following the 2008 financial crisis there was renewed scrutiny of CRAs (Hunt, 2009). The State Attorney General from New York and Ohio headed up an investigation into the potential causes of the crisis (The Economist, 2007; Consumer Bankruptcy News, 2008), the SEC undertook a staff examination of CRA (SEC, 2008) and a report was issued by the international organization of securities commissions (IOSCO, 2008) that offered recommendations on how the existing code of conduct could be modified to improve rating accuracy.[45] In the presence of this increased scrutiny regulators drafted up a new bill aimed at tackling the causes (including issues with the CRA industry) of the financial crisis and chief among these was the Dodd-Frank Act on the 21st July 2010.[46]

At the time of Dodd-Frank there were two schools of thought as to how CRAs should be handled. The first, "gatekeeper" approach favours regulatory changes that reduce the conflict of interest in the CRA market, and the second approach, favoured deregulation and reducing market and regulatory dependence on credit ratings. Coffee (2011) state that the Dodd-Frank act largely straddles this gap and pursues both strategies.

[43] In line with Article 11 and Section E of Annex 1 of regulation 1060/2009.
[44] Article 4.2 and 4.3(a) of EU 447/2012.
[45] This also impacted the CRAs in the EU.
[46] Congress delegated the task of developing specific rules to the Securities and Exchange Commission (SEC).

Chief aspects of the Dodd-Frank act are (i) an increase in CRAs liability for issuing inaccurate ratings and (ii) aiding the SEC to impose sanctions on CRAs and charge them with fraud or misstatements. Firstly, in the EU, CRAs were exempt from being held responsible for their ratings prior to the Dodd-Frank act as CRAs could claim that their ratings constituted an opinion and were therefore protected under the First Amendment as free speech. As such someone bringing a charge against them would have needed to prove that the CRA had issued the rating with the knowledge that it was incorrect or with reckless disregard for their accuracy (Dimitrov et al., 2015). The changes by Dodd-Frank mean that plaintiffs must only be able to prove that the CRA knowingly, or recklessly, failed to conduct a reasonable investigation of the rating security and hence making it easier to bring a case against a CRA for negligence or fraud. Secondly, the Dodd-Frank act makes it easier for the SEC to bring charges against CRAs as under Section 933 it states that CRAs statements are subject to the same laws as equivalent statements from accounting firms or securities analysts and that CRAs statements are no longer considered forward looking. Such penalties include remedial training, fines, censure and losing their licence (Boylan, 2012). These changes make CRAs more accountable for the ratings they produce.

The act contains a series of disclosure requirements aimed at increasing CRA transparency, requiring CRAs to i) file annual reports on internal controls (to the SEC), (ii) disclose rating methodologies,[47] (iii) report the accuracy of past credit ratings and (iv) publicly publish third party due diligence reports. The rules are monitored by the newly established Office of Credit Ratings (established in June 2013) and the SEC now conducts annual reviews of CRAs to ensure the regulations are being followed.

In 2011, the US Senate Permanent Subcommittee on Investigations made several recommendations on how CRAs should be regulated. These followed the same lines as previous reports, that the government should eliminate reliance on credit ratings, increase rating accuracy, transparency and that CRAs should be held more accountable for their ratings. These recommendations cast into law through the 2015 SEC update for nationally recognized statistical rating organizations (NRSROs), which saw a strengthening of internal control structures, measures aimed at tackling conflicts of interests and enhanced performance and methodological disclosure.

[47] The SEC charged the CRA DBRS Inc with misrepresenting its surveillance methodology used in the rating of certain complex financial instruments and settled with a $6 million fine. (SEC press release on 26th October 2015, available from https://www.sec.gov/news/pressrelease/2015-246.html).

The US, like the EU, has tightened the regulation when it comes to CRA. The new changes include increased liability for CRAs, decreasing regulatory and market reliance upon ratings, increased transparency requirements, strengthening of internal control structures and changes that make it easier for the SEC to bring charges against CRAs.

Although the new regulation aims to make it easier to bring charges against CRAs, there have been only a few successful cases and it is still unclear yet how effective this new regulation will be. Numerous questions are still brewing over whether competition should be increased, and the effectiveness of the issuer pays model. But with the failure of the Franken amendment to change the industry model it looks like the current model is here to stay for the time being.

2.3.4 EMPIRICAL STUDIES - THE IMPACT OF EU REGULATION

Much of the European literature has been focused on the impact of sovereign ratings as they played a large role in the EU sovereign debt crisis and can widely effect a countries economy and financial markets (Klusak et al., 2017; Afonso et al., 2012; Ismailescu and Kazemi, 2009; Christopher et al., 2012).

Michaelides et al. (2015) find evidence consistent with information leakage prior to sovereign rating announcements. They argue in favour of the recent EU regulations requiring CRAs to publish their decisions on pre-announced dates, although they highlight the need for regulators to pay attention on how information is transferred between CRAs and local governments to prevent such leakage, particularly in consultation periods. Also, Klusak et al. (2017) investigate the impact of a recent piece of EU legislation requiring CRAs to disclose the solicitation status of sovereigns, which came into effect in February 2011. They show that this stimulated the change in solicitation status of 13 nations in February 2011 and had an adverse impact on intermediaries operating in the country, due to the increased risk transmitting through the sovereign-bank ratings channel.

One of the new initiatives made by the ESMA was the introduction of "identifiers" (on 30th April 2012), which aimed at increasing the dissemination of information to investors (Klusak et al., 2015). The identifiers (EE and EU) inform investors whether a rating originated from inside or outside[48] of the EU, as different regulations apply to each subset. Klusak et al. (2015)

[48] One important requirement of ratings for endorsement is that the analyst is in jurisdictions that has an equivalent regulatory regime to that of the EU (EC, 2011).

examine, using sovereign rating actions from 69 countries in the period 2007 to 2014, whether the ESMA identifiers increase sovereign ratings quality.[49] They find no evidence that ESMA identifiers increase the quality of ratings and that the regulation is ineffective in its goal.

Alsakka et al. (2015) examine whether there are any identifiable differences in market perceptions of rating announcements published by Moody's, S&P and Fitch following the establishment of ESMA in July 2011. They find mixed evidence of the impact of the new regulator, using bank rating announcements and stock returns, on rating quality and market stability, with the results varying across CRAs. Alsakka et al. (2015) conclude that the evidence for increased rating quality and market stability is mixed and that there has most likely been insufficient time (at their time of publishing) since the introduction of the regulation for it to take a strong enough effect. An updated study in the future is highly recommended to see if a clear shift in market perception, rating accuracy and market stability emerges as a result of the regulation.

ESMA published a press release on October 2015[50] that illustrated the key findings and recommendations at this stage (see Table 2.7). It is clear from the press release that the regulation was yet to show a clear impact on competition and conflicts of interest. They make two recommendations, (i) the need for a system of proportionate fines, that can reflect a CRA's turnover and act as an effective deterrent and (ii) further supervisory powers regarding the appointment of independent non-executive directors by CRAs.

2.3.5 Empirical studies - The impact of US regulation

The focus in the US has been on how the Dodd-Frank act has impacted the corporate rating market. Dodd-Frank is Opp et al. (2013) develop a theoretical framework that examines the changing variation in credit rating standards across asset classes and time. They predict that the Dodd-Frank Act will result in a systematic downward shift in the distribution of ratings from CRAs caused by the lowering of regulatory advantages for higher ratings. They also predict that ratings in security classes (i) undergoing rating inflation, will shift to a more conservative outlook and there will be a significant increase in rating informativeness and (ii)

These outside ratings are often endorsed by EU CRAs and Alcubilla and Del Pozo (2012) suggest that endorsement targets CRAs whose ratings are of vital importance to the financial stability of member states.

[49] Their main measure of ratings quality is the link between ratings actions and bond yields.

[50] ESMA sees progress in reform of EU credit rating industry. ESMA/2015/1483 (Vol. 33)

those not undergoing inflation would see a smaller conservative shift and that rating informativeness may decrease.

Dimitrov et al. (2015) analyse Dodd-Frank's impacts on corporate bond ratings. They test two competing hypotheses disciplining and *reputation hypothesis*. Disciplining hypothesis predicts that the regulation improves quality of credit ratings, due to an increase in penalties, both regulatory and legal, that encourage CRAs to invest in providing accurate ratings by improving their methodology, monitoring credit analysts and dedicating resources to improving ratings. *Reputation hypothesis* suggests that optimistic ratings are more likely to be perceived as biased[51] and invite regulatory scrutiny and CRAs hence protect their reputation by lowering ratings beyond a justifiable level. They test these two hypotheses and find no evidence that Dodd-Frank encourages CRAs to provide more accurate ratings, but rather that CRAs tend to issue lower ratings, more false warnings and less informative (smaller market reaction) downgrades. Crucially, they find the result was stronger in markets with greater reputational concerns.

Dimitrov et al. (2015) adapt their measure of reputational concerns from Becker and Milbourn (2011), using Fitch market share. The logic behind which is that the increased presence in a market of a third smaller CRA will stimulate increasingly competitive behaviour by the other two incumbent CRAs. This will correspondingly lead to a decrease in reputation concerns as they seek to maintain market share and hence lead to an inverse relationship between Fitch market share and reputational concerns. Bae et al. (2015) criticize the measure stating that Becker and Milbourn (2011) suffer from two problems firstly, the results are driven by the endogeneity problem caused by unobservable industry effects and secondly that the positive relation between credit ratings and Fitch market share doesn't hold when only firms in non-regulated industries are included in the analysis.[52]

Bedendo et al. (2018) examine the impact of reputational shocks and the information content of ratings. They observe stronger stock market responses to rating downgrades in the aftermath of reputational shocks, as market investors conclude that ratings are generally overstated, following evidence of misrating, and infer greater negative information from downgrades. Examining recent US reforms including the SOX Act, CRA reform act and Dodd-Frank Act, they argue that these seem to improve ratings quality and soften investors responses.

[51] CRAs are more likely to be penalized for optimistically biased than negatively biased ratings (Goel and Thakor, 2011).
[52] This thesis addresses these issues, see Chapter 3 Section 3.3.3.

Other papers touch lightly on the implications Dodd Frank. Bolton et al. (2012) argue that the increased liability introduced could have a significant impact on reducing ratings inflation. However, the number of papers that examine empirically the impact of Dodd Frank on the US rating market is limited. The sweeping reforms are significant, and their impact must be better understood to guide future policy changes.

2.3.6 CONCLUSION

While the regulatory changes have been broad and impacted all credit rating markets, the resultant response from the literature has been more targeted. The European literature has been focused on sovereign ratings, while the US has been focused on corporate ratings. Banks and bank ratings were at the heart of the 2008 financial crisis and if CRAs have truly reformed then there should be evidence of a shift in bank ratings. Yet, there has been little to no examination of this in the literature, there is clear need for a better understanding of how crucial financial institutions ratings have been impacted by the wave of regulation in both the EU and the US.

This thesis focuses on the impact of these regulatory reforms on the EU and US bank rating markets and the subsequent effect on bank behaviour. This will further the understanding about the impact of these reforms.

2.4 THE BANKING INDUSTRY

There is a lot of literature examining different aspects of bank business and behaviour. This Section examines the various key themes in the literature and how bank credit ratings impacts upon them. The literature discussed in this Section is used to justify and design the model used in Chapter 5.

One aspect of banking the literature agrees on, is that banks are profit maximising entities (De Nicolò et al., 2014; Heuvel, 2008; Repullo, 2004; Calem and Rob, 1999), funded by a mixture of debt[53] and equity, who seek to maximise shareholder value, or return on equity, by investing in a mixture of loans and non-interest activities. The proportion of this funding that is equity has important bearings on how financial stable a bank is and is therefore a key consideration for regulators and banks themselves.

2.4.1 OPTIMAL BANK CAPITAL AND CAPITAL REGULATION

A key component of bank behaviour and risk taking is the decision on what level of capital to hold. By holding a lower level of capital, a bank can increase their leverage and potentially make greater profits. The downside of a low capital ratio is that it exposes the bank to a higher level of liquidity risk. Much of the regulatory debate has surrounded the optimal level of bank capital and lead to the new Basel III regulation requiring banks to hold a minimum common equity capital ratio of 4.5% with a capital conservation buffer of 2.5% (EC, 2014).

Correspondingly the literature examines what is the optimal level of capital and there are two key components of the debate. Firstly, how the level of capital will effect bank behaviour and secondly, what levels of capital are best for the economy as a whole. Berger and Bouwman (2013) show that increased levels of capital helps increase small banks survival rates and market share and that it enhances the performance of medium and large banks during crisis periods. Miles et al. (2012) and Bhagat and Bolton (2014) who argue that from an economic point of view, higher levels of capital would create large benefits by reducing the probability of systematic banking crises. They state that their results suggest an optimal level approximately twice as large as the Basel III capital ratio. DeAngelo and Stulz (2015) counter

[53] Where debt is a mixture of bonds and deposits.

this argument, stating that under idealized conditions high leverage is optimal for banks, where there is a market premium for socially valuable liquid financial claims.[54]

While much of the literature (Admati and Hellwig, 2013; Admati et al., 2013; Pfleiderer, 2010; Benhabib, 2016) argues for strong regulatory limits on bank leverage, there are those who question the efficacy of capital requirements. Myerson (2014) argue that the aforementioned case for regulatory limits rests on Modigliani and Miller (1958)'s leverage irrelevance theorem, that states that in perfect markets equity is no more expensive than debt as a source of capital.[55] DeAngelo and Stulz (2015) counter this argument stating that it treats banks as firms that make loans and ignore banks role as producers of liquid financial claims (i.e. providing liquidity to the economy). Many papers (Diamond and Dybvig, 1983; Diamond and Rajan, 2001; Gorton, 2010; Gorton and Pennacchi, 1990; Holmström and Tirole, 1998; Holmström and Tirole, 2011) argue that the idea of liquidity production is intrinsic to financial intermediation (i.e. banking) and banks generate value by producing liquid claims for financial constrained firms and households. They argue that high leverage is optimal for banks, as banks with risky assets use risk management to maximise their capacity to include such debt into their capital structure. Benhabib et al (2016) show that capital requirements and leverage ratios can reduce moral hazard problems, enhance bank stability and eliminate multiple and complex equilibria.

There is also discussion over how the capital requirements should be constructed. Cuoco and Liu (2006) study the behaviour of financial institutions that face capital requirements based on self-reported value at risk (VaR) measures, as in the Basel internal models' approach. They find the VaR capital requirements to be effective at curbing portfolio risk and inducing the disclosure of the risk. The capital requirements based on risk adjusted assets are designed to cover the assets credit risk, while flat minimum capital requirements are supposed to cover market risk. Blum (2008) analyse regulatory capital requirements where the amount of required capital depends on the level of risk reported by the bank. The author shows that if supervisors have a limited ability to detect or sanction dishonest banks, then an additional risk independent leverage ratio restriction may be necessary to induce truthful risk reporting. The leverage ratio helps by increasing the bank's net worth which increases supervisor's ability to sanction banks

[54] Their model also assumes no deviations from Modigliani and Miller (1958) due to agency problems, deposit insurance, taxes, etc.

[55] Admati and Hellwig (2013) state that "increasing equity requirements from 3 percent to 25 percent of banks' total assets would involve only a reshuffling of financial claims in the economy to create a better and safer financial system. There would be no cost to society whatsoever." DeAngelo and Stulz (2015) then argues that if Modigliani and Miller (1958) leverage irrelevance theorem does hold then increasing a bank's equity above 25% would have no social costs.

after the event. Blum (2008)'s model aims to take account of three features of banking that they deem relevant to capital regulation. First, that there is heterogeneity among bank risks, i.e. some banks are risker than others. Second, banks are highly opaque and that while it may be clear *ex post* that a bank incurred high risk, *ex ante* it is very difficult to assess this. Third, that banks have a tendency to hold too little capital relative to their risks.[56]

Bank capital requirements could have a knock-on impact on banks cost of capital. Traditionally the standard Capital Asset Pricing Model (CAPM) predicts that the expected return on a security will be proportional to its systematic risk, or the market beta, and hence as banks become riskier their cost of capital will increase. However, Baker and Wurgler (2015) find that at low risk level, weighted average cost of capital becomes inversely related to leverage.[57] Their findings suggest that a large increase of bank capital requirements could, via the low risk anomaly, significantly increase a bank's cost of capital.

The cost and speed of recapitalization can impact banks optimal capital ratios. Peura et al. (2006) study optimal bank capital choice as a dynamic trade-off between the opportunity cost of equity, the loss of franchise value following a regulatory minimum capital violation and the cost of recapitalization. They introduce a recapitalization delay that causes an increase in the probability of a bank violating the capital adequacy limit and calibrate their model to the data. They find that differences in return volatility explain a significant fraction of the cross-sectional variation in bank capital ratios and that capital market imperfections also play a role in determining the value of bank capital ratios.

The cost of equity capital can exceed that of deposits and deposit insurance can play a role in determining the optimal level of capital. Allen et al. (2015) examine the impact of deposits, equity markets and bankruptcy costs on firm financing under general equilibrium. They show that in equilibrium, equity capital has a higher expected return than investing directly in the risky asset and that deposits are a cheaper form of finance as their return is below the return on the risky asset. The implication being that equity capital is costly relative to deposits. However, they find that when banks directly finance risky investments, they hold a positive amount of equity capital as a way to reduce bankruptcy costs. Allen et al. (2015) go on to explore the impact of capital regulation. In their baseline model (with no deposit insurance) they find there are no benefits from regulating bank capital, as the market solution is efficient. However, the

[56] This is down to limited liability and negative externalities and as such banks don't take into account all the costs that will face third parties in the event a bank default.
[57] They look at a large sample of US banks and find that bank equity risk increases with leverage.

result is different once deposits are insured because then banks no longer have any incentives to hold capital and the market solution is inefficient. They find that capital regulation restores efficiency and improves upon the market outcome.

There is also debate over whether capital requirements should be flat or procyclical. Repullo and Suarez (2013) examine this by employing a dynamic equilibrium model of relationship lending to compare the impact of various bank capital regulation regimes. In their model banks cannot access the equity markets every period and the business cycle determines loan's probability of default. In their model, banks hold endogenous capital buffers to protect against shocks that could impair their future lending capacity and use this to examine the Basel I and II capital requirements. Basel II requires varying levels of capital that depend on the business cycle and in recessions, when losses erode bank capital and risk-based capital requirements become higher, banks cannot quickly raise sufficient new capital and their lending capacity falls. Alternatively, if capital requirements are relaxed to reduce the contractionary effect on the credit supply in bad times, this may increase bank failure probabilities precisely when they are largest (due to high loan defaults). Repullo and Suarez (2013) therefore argue that Basel III seems to be a compromise between the two conflicting goals.[58] The regulation reinforces the quality and quantity of minimum capital required by banks and consists of two buffers: (i) a capital preservation buffer and (ii) a countercyclical buffer that can be built up in good times and released in bad. Shim (2013) also agrees that during crisis periods it is beneficial to enact a counter cyclical capital requirement policy.

Regarding the cost of bank failure Heuvel (2008) examines the welfare cost of capital adequacy regulation. Employing a general equilibrium growth model, they show that capital requirements can limit the moral hazard on the part of banks, but that it can also reduce the ability of banks to create liquidity.

After the financial crisis of 2008 and with the advent of new regulation bank capital ratios have changed. A paper by Cohen and Scatigna (2016) finds that bank capital ratios in the aftermath of the financial crisis have increased steadily. The authors state that retained earnings account

[58] Repullo and Suarez (2013) argue that if the social cost of bank failure is large (as demonstrated by the recent crisis), then higher less cyclically varying capital requirements are required. Hence Basel III may be considered a move in the right direction.
Previously, Repullo (2004) had (utilising a theoretical dynamic model of imperfect competition in banking where banks can invest in a prudent or a gambling asset) shown that either flat-rate capital requirements or binding deposit rate ceilings can ensure that there exists a prudent equilibrium, but that both have a negative impact on deposit rates. This negative impact does not occur when a risk-based capital requirement is used and that it is effective in controlling risk-shifting incentives.

for the majority of the higher risk weighted capital ratios and that reduction in risk weights is a much smaller factor. They explain that on average banks have continued to expand their lending, although in the EU lending has contracted. They also argue that lower dividend pay-outs and, in more advance economies, wider lending spreads has contributed to banks' ability to retain earnings to build capital. Cohen and Scatigna (2016) conclude that banks which emerged from the crisis with higher capital ratios and stronger profitability, were able to expand their lending.

2.4.2 CREDIT RATINGS AND CAPITAL STRUCTURE

To understand the reasons why banks choose to solicit a rating it is necessary to understand the relationship between credit ratings and capital structure. Kisgen (2006) examines to what extent credit ratings directly affect capital structure decisions.[59] They state that managers appear to take credit ratings into account when making capital structure decisions and provide multiple examples of companies restructuring debt in an attempt to maintain or strengthen their credit rating. This result matches that of Graham and Harvey (2001) who found that the second highest concern for CFOs when determining their capital structure is credit ratings and that credit ratings ranked as a higher concern than many factors proposed by traditional capital structure theories.

Ratings can also provide information to investors and provide signals as to the firm's quality (Kisgen, 2006). Therefore, if the market treats ratings as informative, firms will be pooled together according to their rating and thus changes in a firm's rating will result in discrete changes in a firm's cost of capital. A decrease (or increase) in a firm's rating can trigger events that result in discrete costs (benefits) for a firm, these could include change in bond coupon rate, loss of access to commercial paper market (Kisgen, 2007)[60] or loss of a contract. Kisgen (2006) find that concerns for the benefits (cost) of rating upgrades (downgrades) directly affect managers capital structure decisions.[61]

[59] They outline the discrete costs (benefits) associated with firm credit rating level differences and test whether worries over the costs (benefits) directly affect debt and equity financing decisions.
[60] Kisgen (2007) discuss how access to the commercial papers (CP) market is vital source of firm's short-term capital and how access to this market is directly affected by a firm's credit rating. They state that in 2000 99% of CP had either A1 or A2 ratings (S&P) and that the spread between them could be as high as over 100 basis points. Having a rating bellow this would severely limit a firm's access to the CP market for short term debt.
[61] Kisgen (2006) also find that firms that have a credit rating with a plus or minus (e.g. AA-) issue less debt than those without.

An important factor to consider is whether firms target credit ratings or leverage levels. Kisgen (2009) shows that firms reduce leverage following credit rating downgrades (~1.5%-2% less net debt to net equity in the following year).[62] They also show that rating upgrades have no impact upon subsequent capital structure activity, implying that firms target minimum rating levels.

Adjustments to credit rating levels can have a knock-on impact to firms capital structure and investment decisions. Kisgen (2012) analysed the changes Moody's made in 2006 to their adjustment methodologies and found that they significantly affected capital structure and investment decisions in 2007.[63] These results demonstrated that changes in CRAs behaviour can affect firm financing and investment policies.

Ratings also have a great impact on a bank's cost of debt which can affect capital structure decisions. Ratings determine whether a bank's bonds (i.e. debt issued) are classified as investment grade or high yield (junk) (Bongaerts et al., 2012). Lower demand for high yield bonds (debt) can significantly increase a firms cost of borrowing (Krylova, 2016) and hence it affects a firm's capital structure decisions (Kisgen, 2006; Kisgen, 2009; Kisgen and Strahan, 2010; Ellul et al., 2011).[64]

There is much evidence to show that ratings are linked in several ways to capital structure decisions. Therefore, to correctly examine the impact of capital regulation it is necessary to also consider the role of bank credit ratings and vice versa.

2.4.3 HOW BUSINESS MODEL AND SIZE AFFECT PERFORMANCE

Income diversification and the shift to increased non-interest income (changing business models) can have a significant impact on a bank's performance. Shim (2013) shows that a shift towards non-interest income and diversified revenue portfolios offers potential diversification benefits from broader sources of operating revenue with reduced profit volatility and portfolio risk. Brighi and Venturelli (2014) find that larger banks are more successful at increasing their risk adjusted profitability through income diversification. Demirgüç-Kunt and Huizinga (2010)

[62] The effect is greater if the downgrade is to a speculative grade rating and if commercial paper access is affected. These firms are approximately twice as likely to reduce debt as other firms.
[63] Especially for firms near the investment grade boundary.
[64] Kisgen and Strahan (2010) find a clear link between rating changes and firms debt cost of capital. They examine ratings from Dominion Bond Rating Service (DBRS) and find that a one notch higher DBRS rating corresponds to a 39 basis point reduction in a firm's debt cost of capital. Krylova (2016) reports that on average between January 2007-February 2013 a notch upgrade decreases the corporate bond spread by 24 basis points.

find that a shift towards non-interest income generating activities tends to increase the return on assets, but only offers diversification at very low levels. They conclude that strategies focused on generating non-interest income are highly risky. Counter to this, Abedifar et al. (2018) find that non-interest activities have no adverse influence on bank credit risk. To summarize, a bank's business model is intrinsically linked to its risk level and its potential profitability.

The size of a bank is linked to its profitability. Haan and Poghosyan (2012) find that bank size reduces returns volatility, although in a non-linear fashion i.e. that when bank size increases past a certain limit ($5b) it becomes positively related to earnings volatility. They also found that the recent financial crisis decreased the threshold at which the impact of size on returns volatility becomes positive.

A number of papers have attempted to classify banks into different types of business models. Firstly, Roengpitya et al. (2014) identify three business models (i) retail-funded commercial bank, (ii) wholesale-funded commercial bank and (iii) capital markets-oriented bank. Models (i) and (ii) vary chiefly in terms of a banks funding mix, while model (iii) differentiates itself because of banks increased engagement in trading activities (non-interest income). They conclude that banks that engage in predominantly commercial banking activities have lower costs and more stable profits than banks which are heavily involved in capital market activities such as trading.[65] Secondly, Ayadi and De Groen (2014) who focus exclusively on European banks identify four types of banks (by splitting retail into two categories diversified and focused): (i) investment, (ii) wholesale, (iii) diversified retail and (iv) focused retail. They vary in size, funding sources, business activities and capital ratios (see Table 2.8).

The variation in, and impact of, bank size and business model highlight the need for understanding the relationship and ensuring that any simulated panel of banks is heterogeneous in size and business model.

2.4.4 THE BAIL-IN REGULATION

In the aftermath of the financial crisis there was much criticism over the decision to bail-out the banks, in particular it led to an increase in bank risk taking behaviour (Dam and Koetter, 2012) and to an increase in sovereign credit risk (Acharya et al., 2014). Dam and Koetter (2012)

[65] They also find that retail banking has gained ground after the financial crisis, reversing the pre-crisis trend.

employ a structural econometric model to show that safety nets, e.g. government bail-outs, lead to additional bank risk taking. They exploit the fact that regional political factors explain bank bailouts but not bank risk to show that changes in bailout expectations can have an economically significant impact on the probability of bank distress. Acharya et al. (2014) shows that a distressed financial sector induces government bailouts, which result in increased sovereign credit risk. This in turn weakens the financial sector by damaging the value of government guarantees and bond holdings. They term this the sovereign-bank loop.

Due to the issues that arose because of the subsequent bail-out, European regulators decided to institute new regulation under the EU Bank Recovery and Resolution Directive (BRRD) and the Single Resolution Mechanism (SRM) which both came into force on 1st January 2015. This followed on the heels of US regulators who imposed the Orderly Liquidation Authority (OLA) (a type of bail-in that was part of the Dodd-Frank Act in 2010).[66] This new European regulation contained a bail-in tool (applicable since 1st January 2016), which provides the resolution authorities with the statutory power to write down and convert into equity the claims of a wide range of creditors (Hüser et al., 2018).[67] The aim is to shift the penalty for bankruptcy from the tax payer, through government bailouts, to the equity holders first and the creditors second. The mechanism of the European bail-in is as follows: the bail-in is triggered when a bank suffers a loss bigger than 8% of its assets. This causes a write-down of assets to occur, principally the equity and subordinated debt. Once the write-down has occurred the bank is recapitalised to 10.5% common equity capital ratio (CET1) through the conversion of the remaining subordinated debt and part of the senior unsecured debt. In effect this causes the losses of the bank to first be taken by shareholders and then by its creditors (interpretation adapted from Hüser et al., 2018).

The new bail-in regulation will mean that both shareholders and junior creditors will stand to lose more should the bank become insolvent, thereby having more "skin in the game". With more at stake, shareholders will care increasingly about avoiding insolvency/distress that could incur such losses. Regulators hope that this increased concern by shareholders should translate into reduced risk taking and positively impact bank behaviour.

[66] The OLA is bail-in regulation where insolvent, or distressed, bank's shareholders lose their shares and subordinated debtholders face having a proportion of or all of their debt converted to equity.
[67] This will only occur if: (i) it is possible without public support (i.e. the bank has sufficient loss absorption capacity and can be recapitalized) and (ii) it will not generate significant contagion risk to other banks.

While EU regulators have acted, there is currently no consensus in the literature on how best to design such a regime and when, and how aggressively, regulators should act against such banks (Berger et al, 2018). Preliminary evidence, from Hilscher and Raviv (2014), indicates that a mechanism such as contingent capital or the bail-in could be an effective tool for stabilizing financial institutions and Attaoui and Poncet (2015) show that firm's total market value is larger in the presence of write-down debt. DeYoung et al. (2013) provide evidence that the increased confidence in government intervention, in the form of a bail-out, makes bank's debt holders more risk insensitive, reduces bank's exposure to market discipline and encourages bank managers to take greater insolvency risks. The introduction of the bail-in reduces this safety net for banks and should, through increased insolvency costs, result in lower insolvency rates and a reduced cost to governments (Conlon and Cotter, 2014) and hence taxpayers, resulting in a net positive outcome from a social standpoint. Berger et al. (2018) employ a dynamic model of regulatory design to evaluate the US bail-in regulation under the OLA. They show that only the bail-in provides incentives for banks to rebuild capital pre-emptively during distress (unlike the scenarios of the bail-out or no regulatory intervention).

2.4.5 CONCLUSION

The banking industry is complex with many dynamics at play, with interlinking relationships between bank business model, profitability, risk, capital structure and credit ratings. There is much research into how they relate, and effect, each other, which must be considered when constructing a dynamic model of bank behaviour.

The issue of capital requirements is at the heart of the current regulatory debate. However, while the link between capital structure and credit ratings is well established, the impact of the current and future capital requirements on bank credit ratings has not been examined and remains a gap in the literature. Lastly, the literature is still divided on the potential impact of the newly adopted Bail-In regulation. More research is needed to better understand its potential effect on bank behaviour and how changes in bank default costs can impact capital structure and credit rating decisions.

2.5 STRUCTURAL MODELLING

A key part of this thesis is the construction and application of a dynamic structural estimation to dynamically model bank behaviour (in Chapter 5). This will be the first time a dynamic model of bank behaviour has been estimated and to ensure the strength and robustness of the model the literature on both bank modelling and use of dynamic structural estimation in corporate finance and other areas must be considered. Lastly, this thesis employs the technique of discrete choice dynamic programming from labour economics and so its use in the past is examined.

2.5.1 IN CORPORATE FINANCE

Over the past 25 years, research on dynamic corporate finance has grown dramatically both in the theoretical and empirical literature (Strebulaev and Whited, 2011). The body of literature that utilises dynamic structural estimation to examine firm financing has grown over the past two decades. The first foray into this new area was by Gomes (2001), who constructs and calibrates a dynamic model of firm financing and investment decisions, while in the presence of investment and financing costs. Simultaneously Cooley and Quadrini (2001) also construct and calibrate a dynamic model of firm financing with financial market frictions, industry dynamics and persistent shocks. Cooper and Ejarque (2003) specify and estimate a class of dynamic optimization models where imperfectly competitive firms face financial constraints and use market power to induce the principal link between investment and internal funds. Significantly, they are one of the first in this strand of the literature to calculate standard errors for their parameters (model estimation) following the procedure in Gouriéroux and Monfort (1996). Moyen (2004) models financially unconstrained firms using an exogenously parameterized model. Hennessy and Whited (2005) examines firm leverage utilising a dynamic trade-off model with corporate income tax, financial distress costs, endogenous choice of leverage and equity flotation costs, and then utilise the simulated method of moments (SMM) to estimate the model. Hennessy and Whited (2007) then extend their dynamic model of firm financing to examine the magnitude of financing costs for corporations. Another paper that builds on the work of Hennessy and Whited (2005) is Gamba and Triantis (2008), who further extend the model by changing three key assumptions: (i) they separately control for the borrowing and lending decisions of the firm, rather than tracking only the net balance, (ii) introduce an issuance cost for debt and (iii) capital is sold at a discount to its depreciated value.

These changes let them address the simultaneous existence of debt and cash and explore the interactions between financial and investment flexibility under the more realistic assumption of partial reversibility.

2.5.2 IN BANKING

While there is a rich literature examining dynamic firms' decisions, the literature on dynamic banking decisions is very limited and does not include any estimated dynamic model. The models of banking behaviour present in the literature, are either static, purely theoretical or only perform calibration[68] (DeYoung et al., 2015; De Nicolò et al., 2014; Repullo, 2004; Calem and Rob, 1999). DeYoung et al. (2015) present the only model to conduct an estimation, but it is of a static structural model of bank portfolio lending and show that US community bank reduced their business lending during the global financial crisis. Repullo (2004) constructs a theoretical model of imperfect competition in banking where banks can invest in a prudent or a gambling asset under either a flat-rate/risk-based capital requirements or binding/non-binding deposit rate ceilings. They show that the presence of flat rate or risk-based capital requirements results in a prudent equilibrium,[69] but that the former results in a negative impact on deposit rates.

Calibration is the process matching of small number of moments[70] and does not provide any information about the confidence of the results (i.e. there are no standard errors). On the other hand, a dynamic structural estimation is performed on several moments (usually using SMM or Simulated Maximum Likelihood) and provides standard errors. Estimation is a much more rigorous and comprehensive technique and has become increasingly popular in several areas of economics, including labour economics, and corporate finance. The use of estimation can allow us to explore different mechanisms and to unveil, and better understand, bank behaviour.

De Nicolò et al. (2014), Valencia (2014a), Valencia (2014b), Heuvel (2008), Peura et al. (2006) and Calem and Rob (1999) calibrate dynamic models of banking, where banks are financed by a combination of debt and equity and exposed to shocks. With De Nicolò et al. (2014) examining the impact of micro prudential bank regulations on bank lending in a setting where

[68] Calibration does not involve the calculation of standard errors for the parameter unlike estimation and generally involves much fewer moments and parameters. Theoretical models are not tied to the data and static models cannot capture the changing behaviour of banks over time.
[69] Effective at controlling risk shifting incentives.
[70] A moment is a statistical characteristic of the data (e.g. mean bank size in a period or the standard deviation of ROE).

banks undertake maturity transformation, are exposed to liquidity and credit risks and face financing frictions. They show (i) a U-shape relationship between lending, welfare and capital requirements, (ii) liquidity requirements reduce lending and (iii) resolution policies that depend on observed capital (e.g. prompt corrective action) are much more efficient and are greater in welfare terms than (noncontingent) capital and liquidity requirements. Calem and Rob (1999) calibrate a model of the dynamic portfolio choice problem facing banks to assess the impact of bank capital requirements. They show that as capital increases, banks first take less risk and then more risk and that an increased capital requirement (whether flat or risk-based) induces more risk taking by ex-ante well capitalized banks that comply with the new requirement. Valencia (2014a) develops and calibrates a bank model to study supply-driven contractions in credit, where banks are affected by financial frictions when raising external funds. He finds that banks repair their balance sheet only gradually following a negative shock that weakens the capital position and that it therefore leads to a persistency in the response of bank lending. They find that this causes: (i) bank capital to increase with risk, (ii) negative shocks have a bigger impact on lending than positive ones and (iii) an observed volatility clustering in risk spreads and bank share prices. Valencia (2014b) calibrate a dynamic model of banking to show that with limited liability banks lever up excessively to finance new loans. Heuvel (2008) dynamically models banks to examine the welfare cost of bank capital requirements. He shows that the welfare cost of capital adequacy regulation (Basel I), which reduce banks' lending, was equivalent to a permanent loss in consumption of between 0.1% and 1%.[71] Peura et al. (2006) calibrate a dynamic model of banks to study bank capital choice as a dynamic trade-off between the opportunity cost of equity and loss of franchise value after falling below the regulatory capital requirement and needing to recapitalize. They find that differences in return volatility and capital market imperfections across banks explain much of the cross-Sectional variation in bank capital ratios.

2.5.3 DISCRETE CHOICE DYNAMIC PROGRAMMING

Discrete choice dynamic programming is a modelling technique pioneered by Keane and Wolpin (1994, 2009, 2010) and has been predominantly used in labour economics. It can be estimated using a variety of methods such as the simulated method of moments (SMM)

[71] Heuvel (2008) does admit that bank capital requirements limit the moral hazard on the part of banks which is created by the presence of deposit insurance.

(McFadden, 1989; Pakes and Pollard, 1989) or the simulated maximum likelihood (SML) (as in Sauer (1998) or Lucarelli (2006)) and has the advantage of being able to discover the mechanism that produce observed outcomes (Low and Meghir, 2017), rather than showing only that a relationship exists.

The technique has been used to great effect to examine such topics as volunteering (Sauer, 2015), labour markets (Keane and Wolpin, 2010; Keane and Sauer, 2009; Sauer, 1998) and the link between race and attainment (Keane and Wolpin, 2000). To the best of my knowledge it has not yet been employed in the field of banking.

2.5.4 CONCLUSION

Despite the use of dynamic structural estimation being employed in other areas of finance and economics, it is yet to be applied in banking. This is unfortunate as the field of banking has numerous dynamic models, some of which are calibrated, which could benefit from the application of more robust techniques. The development of such models in banking could be furthered, and improved, by the application of more rigorous estimation techniques (i.e. DCDP). They will help identify both the presence of mechanisms and reveal mechanisms themselves. It is known that there are many dynamics at play within the banking sector and the application of dynamic structural estimation is the most appropriate way to examine such models. In particular they are most appropriate at examining how shocks to the banking system, such as regulatory changes, can propagate, effecting banks and their behaviour through unexpected channels. Furthermore, the added confidence in the results given by the calculation of standard errors will greatly benefit the literature by providing increasingly robust estimates of parameters. This prior absence in the literature leads to a potentially rich new avenue of research.

2.6 CONCLUSION

The literature on the credit rating industry centres around the problems inherent in the issuer pays business model, issues with the methodology and competition within the industry. Many academics have criticised the business model but have been unable to come up with a viable alternative as most would require a substantial market overhaul. The academic community is also divided over whether increased competition would have a positive effect as it may exacerbate the problem of ratings shopping, but the current oligopoly may put too much power in the hands of CRAs.

The recent structured finance crisis highlighted the issues faced by the industry and has led to a number of regulatory reforms in both the EU, under the new CRA I, II and III regulations, and in the US under the Dodd-Frank act. The failings centred on methodological issues (advisory services and working too closely with financial institutions), conflicts of interest inherent in the business model and a reluctance to update ratings on products that were clearly overvalued. During the European sovereign debt crisis, the timing of rating changes was once again condemned and blamed for potentially exacerbating the crisis. This clear failure of CRA not just in Europe but also on the world stage has raised vital questions for regulators, academics and the industry on the best way to adapt the industry to promote more accurate and timely ratings.

The literature examining the European regulatory changes has primarily centred around CRAs role in the EU sovereign debt crisis and how the new reforms may act to prevent a reoccurrence. There is limited literature on how the regulatory reforms will impact corporate and bank ratings. The literature in the US predominantly focuses on the impact of Dodd-Frank on corporate ratings and again neglects to examine the resulting impact on the bank rating industry. This is most likely down to the complicated nature of the bank rating industry due in part to its increased opacity. However, this does not diminish the need for a thorough investigation into how the regulation has influenced bank ratings. This is all the more important because of the pivotal role such financial institutions played in the 2008 financial crisis.

Capital structure plays a key role in the banking industry and is impacted by changes to a bank's credit rating. The recent Basel III capital requirements along with the bail-in regulation will have a profound impact on bank behaviour and decision making. To best understand these intertwining relationships and dynamics, dynamic structural estimation will be employed. This is the first time this has been used in the banking literature as previous dynamic models have been limited to being purely theoretical or in some cases weakly calibrated. The literature in corporate finance and economics has benefited from the application of such models and this thesis will show that it is possible to utilise them in the banking setting.

Empirical Chapter 3 furthers the understanding of the impact of recent EU regulatory reforms on the FI rating market, as previously the EU literature has been focused on the sovereign rating market. Empirical Chapter 4 will examine the impact of the Dodd-Frank Act on the US FI rating market, as previous literature in the US has focused on the reforms effect on the corporate rating industry and neglected the bank rating sector. Empirical Chapter 5 furthers three key areas; (i) firstly, the nock on effect of EU credit rating industry reforms on FI behaviour is considered, (ii) secondly, DCDP is applied to model FI behaviour utilising dynamic structural estimation (which has not been done before) and (iii) two additional key FI reforms (capital requirements and the bail-in regime) and their impact on FI behaviour and FI ratings is considered within the dynamic framework of the model. To summarize, this thesis furthers the literature on the impact of recent regulatory reforms on the FI rating industry and the subsequent effect on bank behaviour.

TABLES

Table 2.1: Summary of literature on CRAs

Paper	Topic	Region (US/EU)	Empirical	Findings
Spatt and Sangiorgi (2015)	Bias		N	Implications for regulatory disclosure requirements
Becker and Milbourn (2009)	Competition	Worldwide	Y	Competition can impede the reputational mechanism
Becker and Milbourn (2011)	Competition	Worldwide	Y	Increased competition from Fitch, results in lower quality ratings, less informative
Bolton et al. (2012)	Competition	Worldwide	N	Competition can reduce efficiency, facilitates rating shopping. Ratings more likely to be inflated in good economic times, as investors more trusting
Camanho et al. (2010)	Competition	Worldwide	N	More competition by itself does little to resolve conflict of interest and doesn't help with current issuer pays model
Faure-Grimaud et al. (2009)	Competition	Worldwide	N	Competition will lead to less information being revealed in equilibrium
Hirth (2014)	Competition	Worldwide	N	Investor type, CRA nature, regulatory intervention and competition.
Mollers and Niedorf (2014)	Competition / liability	EU	N	Calls for civil liability regime, increased competition
Mathis et al. (2009)	Conflict of interest	Worldwide/US	Y	Reputation argument only valid when sufficiently large proportion of CRA income doesn't come from rating complex products. If complex products are, then CRA is always too lax with positive probability and inflates ratings when reputation is good enough. Advocate platform pays model
Coffee (2011)	CRA Reform	US	N	Doubts that reform is possible with current conflict of interest of the issuer pays model. Increased competition may aggravate problem of ratings inflation
Dimitrov et al. (2015)	Dodd-Frank	US	Y	No evidence of increased accuracy.
Klusak et al. (2015a)	ESMA identifiers	EU	Y	ESMA requirement for identifiers has no effect on quality of ratings reported by CRAs
Alsakka et al. (2015)	EU regulation	EU	Y	Mixed evidence of enhance rating quality and enhanced market stability
Michaelides et al. (2015)	Information leakage	Worldwide	Y	Find evidence for information leakage, negatively effects daily abnormal stock index returns, more pronounced in countries with lower institutional quality.
Mathais (2014)	Liability	EU compared to US and Australia	Y	Compares EU, US and Australia CRA liability. New regime in EU is cover up to mask continuing difference between EU member states concerning appropriateness of CRA civil liability

Behr et al. (2014)	Rating quality	US	Y	Defaults and other negative credit events more likely for same rating after the SEC action than before. Effect is stronger for smaller firms as less visible and less likely to harm reputational capital.
Boylan (2012)	Rating quality	US	N	Reforms will be effective at reducing conscious bias but not at reducing unconscious bias. To combat unconscious bias the CRA fee structure, business models and risk-management methods need to be changed
Bayar (2014)	Regulation	EU/US	Y	New regulations (Dodd-Frank and EU) will likely succeed in increasing transparency and accountability for CRA and decrease over reliance on CRA but will not eliminate conflicts of interest completely.
Bai (2010)	Reputation	US	Y	The current disclosure requirements cannot (i) deter conflict of interests and (ii) help new entrants join market. Makes recommendations
Bannier et al. (2010)	Unsolicited ratings	non US	Y	Why unsolicited firm ratings lower than solicited. Ratings concervatism may play a role for industrial firms, strong evidence of ratings conservatism for banks. Downward bias increases with banks opaqueness
Behr and Guttler (2008)	Unsolicited ratings		Y	Unsolicited ratings are less informative.
Behr et al. (2018)	CRAs and regulation	US	Y	1975 reforms of the CRA industry increased barriers of entry and resulted in inflated ratings.
Bongaerts et al. (2012)	Rating shopping		Y	Multiple credit ratings are primarily for regulatory purposes and do not provide additional information.
Byoun (2014)	Unsolicited ratings	Worldwide	N	2 separate equilibria for subscriber pays and issuer pays models. Strong incentive to selectively issue unsolicited ratings to induce more fee based solicited ratings
Byoun and Shin (2012)	Unsolicited ratings	Japan	Y	Unsolicited ratings are lower and induce significant announcement period returns for downgrades.
Byoun et al. (2014)	Unsolicited ratings		Y	Firms with solicited ratings experience positive (negative) abnormal stock performance following rating upgrade (downgrade), while unsolicited firms experience zero abnormal stock performance. The difference reflects the difference in information public and private against public. No evidence of downward bias in ratings
Fulghieri et al. (2014)	Unsolicited ratings	US	N	Issuing unsolicited ratings can punish those who do not purchase one and used to extract higher fees
Han et al. (2012)	Unsolicited ratings	Japan	Y	Firms with solicited ratings differ from those with unsolicited ratings. Companies with solicited ratings have less information asymmetry and are more likely to be owned by foreign investors, generate more revenue from exports, be cross-listed in the US, and have higher firm quality. Companies with

				unsolicited ratings pay higher costs for debt, and their bond prices react more strongly to credit-rating changes. Yield spreads for bonds with unsolicited ratings are higher
Poon and Firth (2005)	Unsolicited ratings	World	Y	Unsolicited ratings are for companies that are smaller and have weaker financial profiles
Klusak et al. (2015b)	Unsolicited sovereign ratings	EU	Y	Switch to unsolicited by a number of countries due to the disclosure regulation, caused a downgrade which effected banks

The table reports summary of studies investigating CRA and their behaviour.

Table 2.2: Categorization of credit rating studies by topic

Topic	Subtopic	Empirical Studies	Non-empirical with theoretical model	Discussion Papers
Competition		Becker and Milbourn (2011)	Bolton et al. (2012) Hirth (2014) Camanho et al. (2010)	Coffee (2011) Dittrich (2007)
Ratings shopping			Faure-Grimaud et al. (2009) Skreta and Veldkamp (2009)	
Issuer pays model and conflicts of interest			Spatt and Sangiorgi (2015) Camanho et al. (2010) Stopler (2009)	
Reputational capital		Mathis et al. (2009)		Coffee (2011)
Unconscious bias				Bazerman et al. (2002) Boylan (2012)
Solicited vs Unsolicited ratings		Bannier et al. (2010) Bongaerts et al. (2012) Byoun et al. (2014) Han et al. (2012) Klusak et al. (2015b) Poon and Firth (2005) Poon et al. (2009) Poon (2003) Roy (2013)	Byoun (2014) Fulghieri et al. (2013)	
Ratings quality post regulation	EU	Alsakka et al. (2015) Klusak et al. (2015a)		Mollers and Niedorf (2014) Utzig (2010)
	US	Dimitrov et al. (2015)		
	Both	Bayar (2014) Hau et al. (2013)		
Sovereign ratings				De-Haan and Amtenbrink (2011)

The table provides a summary of studies and categorizes them into the different topics covered.

Table 2.3: Summary of studies on solicited versus unsolicited ratings

Paper	Employs empirical data	Model type	Finds unsolicited ratings are lower	Unsolicited ratings effect on informativeness
Bannier et al. (2010)	Yes	Pooled Logit regression model with random effects	Yes	+
Bongaerts et al. (2012)	Yes	Cox proportional hazard model	Yes	Mixed
Behr and Güttler (2008)	Yes	Trade-to-trade approach (market model)	Yes	+
Byoun and Shin (2012)	Yes	Probit model	Yes	Mixed
Byoun et al. (2014)	Yes	Two factor model	Yes	Mixed
Fulghieri et al. (2013)	No	Dynamic rational expectations model	Yes	-
Han et al. (2013)	Yes	Probit model with a linear regression	Yes	Mixed
Klusak et al. (2017)	Yes	Ordered probit model and difference in estimation	N/A	-
Poon and Firth (2005)	Yes	Two step treatment effects model comprising the Heckman two step estimation	Yes	Mixed

The table reports a list of studies that focused on unsolicited ratings. It is clear from the studies that unsolicited ratings are typically lower due the type of firm targeted by CRAs for unsolicited ratings (due to sample selection bias). However, it is much less clear from the literature if unsolicited ratings provide extra information to the market or whether they are simply a tool used by CRAs to elicit higher fees. ' +' represents a positive effect, and ' –' represents a negative effect of unsolicited ratings on *rating informativeness.*

Table 2.4: List of studies on competition in the rating industry

Paper	Effect of competition on ratings quality
Becker and Milbourn (2009)	-
Faure-Grimaud et al. (2009)	-
Camanho et al. (2010)	-
Becker and Milbourn (2011)	-
Bolton et al. (2012)	-
Coffee (2011)	Mixed
Dittrich (2007)	+
Möllers and Niedorf (2014)	+

The table provides a summary of papers that examine competition and their view on its impact on ratings quality. There is substantial evidence in the literature for the negative effect of competition on ratings, which calls into question why regulators seek to promote increased competition. ' +' represents a positive effect, and ' –' represents a negative effect on rating quality.

Table 2.5: ESMA (2015a)'s review of CRAs methodologies

Category	Findings
Discriminatory Power	Broad variation in the extent in which CRAs demonstrated the discriminatory power of their methodologies in a quantitative fashion. One or more CRAs demonstrated the discriminatory power of their methodologies using the Accuracy Ratio (AR^2), other CRAs used the average ratings in time periods before default. One or more CRA found it challenging to perform tests to confirm the discriminatory power of the methodologies, even though the ESMA considered there to be sufficient quantitative evidence. Other techniques used included confidence intervals (including bootstrapping technique)
Predictive power	CRAs cited challenges in measuring predictive power.[72] The main test used by CRAs to assess the predictive power of their methodologies is the Binomial test. One or more CRA used internal thresholds to assess the performance of the predictive power of their methodologies. Some CRAs used multiple techniques (which include the Hosmer-Lemeshow Chi-Square test, the Normal test, the Brier Score and a test that compares the 3 year cumulative default rates to the ECAIs[73] monitoring level benchmarks of Basel II.
Historical Robustness	The vast majority of CRAs referred to transition studies to demonstrate the historical robustness of their methodologies. Additional measures are performed, including reviews of large movements and reviews of ratings that were downgraded from investment grade to non-investment grade. These measures are typically more qualitative than quantitative and as such CRAs typically don't have any thresholds in place.[74] One or more CRAs used at least two of the techniques identified.

The table reports the findings of ESMA (2015)a *Section 4.1. The report investigates the current state of CRAs' methodologies which are employed when there is sufficient quantitative evidence to make rating decisions.*

[72] CRAs cited the argument that their ratings are based on an ordinal (rather than cardinal) scale and that the behaviour of rating categories is not fixed as it relates to economic and other factors.
[73] External Credit Assessment Institutions.
[74] However, some CRAs do use thresholds for stability measures using statistics calculated from transition matrices.

Table 2.6: Key points in the EU regulation

EU	Regulation	Summary	Date Implemented
2009 EU No 1060/2009	Article 6	A credit rating agency shall take all necessary steps to ensure that the issuing of a credit rating is not affected by any existing or potential conflict of interest.	16th September 2009
	Article 7	Ensure the competency and un bias of their staff. Rating analyst's bonuses cannot be contingent on the amount of revenue they derive.	
	Article 8	Disclosure of rating methodologies and assumptions. Ensure that said methodologies are up to date and to a high and rigorous standard. Establishing internal control structures. They cannot refuse to rate an entity just because it is rated by another CRA. Must review its methodologies annually. Any update to its methodologies requires immediate disclosure, assessment of which ratings could be affected and then updating those ratings.	
	Article 10	CRAs must disclose all ratings and any decision to discontinue a rating. They must disclose their unsolicited ratings policy and whether the entity participated in the rating and whether they had access to the accounts.	
	Article 11	Must publish historical rating performance.	
	Article 12	A CRA must publish annual transparency reports.	
	Article 14-20	Process for registering CRAs.	
	Article 23	New powers for the regulator.	
	Article 24	New powers for the member states, including withdrawing registration of the CRA.	
	Article 26-33	Cooperation with authorities.	
	Article 36	Penalties for CRAs.	
2013 EU No 462/2013	Article 5c	Credit rating agencies shall establish, maintain, enforce and document an effective internal control structure governing the implementation of policies and procedures to prevent and mitigate possible conflicts of interest	21st May 2013
	Article 6	Further strengthening of the conflict of interest preventions. Instigates a four-year rotation policy for re-securitisations.	
	Article 8	Further strengthening of disclosure requirements.	
	Article 35a (1)	An investor or issuer may sue a CRA for damages, if it can be shown that the had intentionally, or because of negligence, committed an infringement listed in Annex III. An investor may claim damages if they have used a rating in a decision to invest into or divest from a financial product covered by that credit rating. An issuer may claim damages where it or its financial products are covered by that credit rating and the infringement was not caused by inaccurate, or misleading, information provided by the issuer to the CRA.	

Summary of the EU regulations published in 2009 and 2013.

Table 2.7: Summary of the reforms progress, an ESMA (2015b) review

Findings	Recommendations
Most CRAs (excluding the big three) tend to be specialised (asset class or member state) and as a result the dynamics of the CRA industry are more complex than they initially anticipated.	Further supervisory powers regarding the appointment of independent non-executive directors by CRAs
There is little effective competition in certain market segments, as the fees tend to be high and there is regular fee increases by selected CRAs.	All requirements of the CRA regulation should have corresponding infringement.
The measures to stimulate competition and improve investor confidence have had little impact as of the report.	Fines should better reflect a CRAs turnover to ensure they have a proportionate effect (deterrent) on CRAs of varying sizes.
The mandatory rotation of CRAs (for selected re-securitisations) has not yet been used in practice.	
The requirement of multiple credit ratings for structured financial instruments has had little impact as this was already standard industry practice.	
References to national banks still remain in national and EU legislation (including some central banks collateral framework).	

Summary of the findings and recommendations of the ESMA (2015b) review into the progress of the reforms.

Table 2.8: Bank types

Type	Size	Funding	Activities	Tangible common equity ratio
Model 1 – Investment	Largest.	Less stable and less traditional sources such as debt liabilities and repurchase agreements. Customer deposits 23.1%.	Substantial trading activities and derivative exposures (51.2% and 15.2% of total assets respectively).	Highly leveraged, 3.9%.
Model 2 – Wholesale	Smallest and declined over time.	Heavy reliance on interbank funding and lending. The liabilities to this bank model to other banks (including deposits and interbank debt) represent 37.4% of total balance sheet. Traditional customer deposits around 16.0% of balance sheet.	Active in non-traditional uses, including trading assets (28.1% of balance sheet) and interbank lending (38.4% of total assets).	Less leveraged, 5.9%.
Model 3 – Diversified retail	Medium, grow during the crisis.	Greater reliance on debt markets. Customer deposits 34.2%	Customer loans and debt liabilities account for 48.0% and 67.5% of total balance sheet on average.	4.7%
Model 4 – Focused retail	Small.	Primarily customer deposits 62.8%.	Customer loans represent on average 60% or more of the balance sheet.	5.5%

Ayadi and De Groen (2014) classification of the four types of EU banks. The numbers quoted are from the information provided in Ayadi and De Groen (2014) Table 3.2.

Regulating rating agencies: A conservative behavioural change

Chapter 3

3.1 INTRODUCTION

The US sub-prime crisis led to increased public and regulatory scrutiny of the quality of ratings issued by credit rating agencies (CRAs) (e.g. Bae et al., 2015; Flynn and Ghent, 2018). High quality ratings are vital for the proper functioning of the financial system, given that credit ratings are heavily used by regulators, debt issuers, investors and financial institutions (Becker and Milbourn, 2011; EC, 2016). In response to the sub-prime crisis, the EU acted promptly to establish new regulations for CRAs operating in Europe (see Section 2.3.2). The key aim of this Chapter is to investigate the impact of the EU regulatory reforms on the quality of ratings. This Chapter focuses on two dimensions of rating quality: (i) the ability of ratings to classify risk, and (ii) their ability to transfer information to market participants. Ratings that can correctly classify the future probability of defaults and are closely correlated with current market prices fulfil their expected functions. Inflated ratings (overstatements of creditworthiness) mislead the market regarding the true financial condition of a debt issuer. It is now evident that inflated ratings (especially in structured finance products) were prevalent prior to the global financial crisis, with the most notable example being Lehman Brothers' AAA rating months before its financial collapse (see Section 2.2.10). Steps to discourage rating inflation could therefore potentially enhance ratings quality. However, the increased regulatory scrutiny, liability and penalties could cause a shift to more conservative rating behaviour (Bannier et al., 2010).

The initial stage of EU CRA regulation was established in September 2009 (No 1060/2009, known as CRA I, see Section 2.3.2) and sought to address conflicts of interest in the rating process through comprehensive disclosures by CRAs of their rating models, historical performance and annual transparency reports. In July 2011, the newly created European Securities and Markets Authority (ESMA) assumed responsibility for supervising and certifying CRAs operating in the EU (CRA II). ESMA sought to mitigate mechanistic reliance on credit ratings by market participants, and thereby reduce the potential for market overreactions to rating actions (EC, 2014). These regulatory reforms mark a shift from the pre-crisis scenario of CRA self-regulation and towards stringent regulation enforced by ESMA. Prior to this, the scope for legal and regulatory fines on CRAs was much more limited and no entity had direct responsibility to ensure that the regulation was implemented. This is the most significant factor that should contribute to a decrease in rating inflation. The May 2013 regulatory update (CRA III) strengthened the regulation with the instigation of a new civil liability regime and expansion of the transparency and monitoring requirements. Overall, the key aims of the regulation are to increase the quality of ratings by reducing rating inflation, to increase the informativeness of rating upgrades, and to reduce mechanistic market reactions to rating downgrades.

This hapter contributes to knowledge in two respects. First, it investigates whether the EU regulation has achieved its stated objectives. Second, it focuses on the behaviour of ratings of financial institutions (FIs), given their pivotal role before and during the global financial crisis. FIs are also opaque and subject to a range of different risks, which make them more difficult to rate by CRAs compared with firms in other industries (Flannery et al., 2013; Morgan, 2002). Also, FI ratings affect the cost of borrowing and they are key determinants of the quality of FIs' portfolios, the quality of collateral to obtain liquidity from central banks, and capital adequacy requirements. This Chapter provides evidence on FIs' ratings following changes to CRA regulation, an aspect which is neglected in the earlier literature. The sample includes ratings from the largest three CRAs (Moody's, S&P and Fitch) for 758 FIs across 27 European countries during the period January 2006 to June 2016.

Three hypotheses on the impact of the regulatory change on credit ratings are tested, namely the *disciplining*, *conservatism* and *reputation* hypotheses. The *disciplining hypothesis* suggests that the regulation succeeds in the objective of increasing rating quality, on the grounds that increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring (Bae et al., 2015; Dimitrov et al., 2015). The regulation also promotes the disclosure of conflicts of interest, strengthening of CRAs' internal control structures and increasing transparency (see Section 2.3.2).

The *rating conservatism* hypothesis stems from Bannier et al. (2010) who show that CRAs are exposed to more severe scrutiny and penalties by over-rating (being less conservative), rather than by under-rating (being more conservative). As a result, increased regulatory stringency, fines and liability can cause a shift to more conservative rating behaviour. They also find that the effect is stronger in more opaque settings (such as FIs). With the new regulation increasing the potential penalties for over-rating, there may be a corresponding increase in conservatism. While the regulation discourages optimistic ratings bias, it does not equally punish pessimistic rating bias (under-rating), i.e. a rating that is too generous is much more likely to incur scrutiny and criticism than a rating that is too low, and thus CRAs may choose to err on the side of caution.[75] If CRAs downgrade issuers simply to avoid potential regulatory and legal penalties, then one would expect these rating downgrades to be unjustified and hence less informative to the market. Importantly, this effect should vary only with regulatory stringency and issuer opacity, while should not be affected by reputational concerns. Further, this Chapter argues that conservatism is more observable in FI ratings. Bannier et al. (2010) find that the strength of the conservatism increases when the issuers' creditworthiness is more uncertain, i.e. the firms are more opaque. While Flannery et al. (2013), Iannotta (2006) and Morgan (2002) show that FIs have greater information opacity than firms in other industries. FIs should therefore exhibit greater *rating conservatism* if it is present.

The *reputation hypothesis* implies that CRAs may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FIs' financial characteristics, in order to protect and rebuild their reputation (Dimitrov et al., 2015; Bedendo et al., 2018; Flynn and Ghent, 2018). Crucially, if the *reputation hypothesis* is confirmed, its effect should be stronger in market segments where CRAs care more about their reputation (see Section 3.3.3). Three key indicators are tested: rating levels, the number of false warnings and the informational content of rating announcements. The precise predictions made by each of the three hypotheses are detailed in Section 3.4.4.

This Chapter also furthers the debate surrounding the most appropriate mechanisms for regulating CRAs in the future. The results show that the recent EU regulatory actions have largely been successful in reducing rating inflation and have led to a significant decrease in rating levels, as predicted by the regulators surveyed in EC (2016).[76] However, the increased regulatory scrutiny has changed CRA behaviour whereby ratings are increasingly conservative.[77] This causes an increase in unwarranted downgrades and false warnings, which in turn contribute to an observed decrease in the market reactions to rating downgrades (less informative downgrades). There is some evidence that rating upgrades are more informative in the post-regulatory period, particularly those by S&P and Fitch. This is consistent with increased *rating conservatism* since CRAs expend greater effort to ensure that each upgrade is

[75] Obviously, there could be opposing views for a debt issuer and investor, e.g. issuers will be more relaxed about generous ratings.
[76] Both CRAs and issuers surveyed in EC (2016) were much more sceptical about the potential impact of the regulation than were the regulators.
[77] This is not the first time that CRA regulation has produced unintended consequences (see Behr et al. (2018).

warranted. The findings also show that the EU regulatory update in May 2013 acted to strengthen the existing impact of the regulation.

The Chapter's results contrast with those reported by Dimitrov et al. (2015) for the US corporate rating market following the Dodd-Frank Act (DFA). They study the impact of the DFA on US corporate ratings (excluding FIs) and find no evidence of increased *disciplining* or *rating conservatism*, but that CRAs become more protective of their reputation. Therefore, this Chapter's findings imply that there are unique effects in the EU and FI contexts. The EU and US CRA regulations have some similar objectives, but they differ in the details and the execution (see Section 2.3.3). ESMA has been much more active in enforcing its new regulatory regime than has the US Security and Exchange Commission (SEC). ESMA has issued three fines to CRAs for breaches of the new regulation, while the SEC has yet to do this.[78] The Chapter's results are robust to consideration of the DFA timing (see Section 3.5.4), and there is a clear incremental effect of the additional EU regulation when CRA II and CRA III are implemented in July 2011 and May 2013.

The Chapter is laid out as follows. Section 3.2 details the literature and prior research into the impact of regulation on CRAs. Section 3.3 describes the data and variables used. Section 3.4 details the model and methodology. Section 3.5 describes the empirical results and discusses them, and Section 3.6 concludes.

[78] DBRS was fined €30,000 on 29th June 2015 for failing to comply with corporate governance, compliance and record-keeping requirements. Fitch was fined €1.38 million on 21st July 2016 for negligence, transmitting information about upcoming rating actions and internal control failures. Moody's was fined €1.24 million on 1st June 2017 for negligence regarding their public announcements of ratings and public disclosure of methodologies.

3.2 LITERATURE REVIEW

The business model adopted by CRAs is predominantly the "issuer pays" approach, whereby the issuer is charged for receiving a rating on a debt issuance. Issuers can be assumed to prefer favourable over truthful ratings and, since it is the issuer who pays fees to the CRA, there exists an inherent conflict of interest (see Section 2.2.1). This could be even more problematic in a context of competition for rating business, as discussed later in this Section (and in Section 2.2.3). CRAs argue that the main incentive for them to provide honest and accurate ratings is their concern for their reputation (Bar-Isaac and Shapiro, 2013). Some researchers propose that CRAs possess "reputational capital" (Flynn and Ghent, 2017; Lugo et al., 2015), whereby CRAs may enhance their reputation by rating accurately, so that they can take future opportunities to inflate ratings to increase revenues. Bedendo et al. (2018) argue that reputational shocks, such as the sub-prime crisis and the lawsuit against S&P,[79] cause the depletion of CRAs' reputational capital and thus trigger a period of reputation building which is characterised by more conservative ratings with less informational impact in financial markets (see Section 2.3.5).

Competition in the rating industry also impacts upon the quality of ratings issued. This theory is tested by both Becker and Milbourn (2011) and Dimitrov et al. (2015) who examine the entry of a third CRA (Fitch) into the US corporate bond rating market (see Section 2.2.3). They find that increased competition from Fitch coincides with lower quality ratings from incumbents (Moody's and S&P), as a consequence of inflated corporate rating levels. Similar findings are reported for structured finance ratings. Cohen and Manuszak (2013) investigate the competition effects on AAA-rated tranches of commercial mortgage-backed securities. Similar to Becker and Milbourn (2011), they provide evidence that competitive pressure from Fitch results in more lenient ratings assigned by the incumbents (Moody's and S&P). Such effects of competition were more pronounced when Fitch's market share was low, but disappeared after Fitch became more established. Flynn and Ghent (2017) also analyse the entry of new CRAs into the structured finance rating market and find evidence to support Becker and Milbourn (2011). Griffin and Tang (2012) also provide evidence on rating inflation in the

[79] The 2013 civil lawsuit by the US Government's Department of Justice and District of Columbia against S&P for defrauding investors in structured financial products, by issuing inflated ratings that misrepresented the true risks of the securities (Bedendo et al., 2018). The US government entered into a \$1.375 billion settlement agreement with S&P in 2015. This was not an action taken by the US SEC.

structured bond market. Morkoetter et al. (2017) find that increased competition among CRAs increases the rating effort of each individual CRA such that more information is created for market participants. Hirth (2014) states that the implementation of performance monitoring and punishment by a regulator rather than by investors can lead CRAs to become more honest.

Prior research has also considered the impact of US CRA regulation, chiefly the provisions within the DFA (see Section 2.3.5). Opp et al. (2013) develop a theoretical framework which predicts that the DFA would result in a systematic downward shift in the distribution of ratings from CRAs, caused by the lowering of regulatory advantages for higher ratings.[80] Dimitrov et al. (2015) empirically analyse the impact of the DFA on corporate bond ratings. They use Fitch market share across industries as a proxy for reputational concerns (drawing from Becker and Milbourn, 2011) to distinguish between industries with stronger and weaker reputational concerns. They find that the introduction of the DFA induced a reduction in rating levels, as predicted by Opp et al. (2013). The frequency of false rating warnings increased and the stock and bond market impact of rating downgrades diminished, i.e. rating downgrades became less informative. They report that all the above findings are stronger in industries where reputational concerns exist for CRAs. These results are consistent with the *reputation hypothesis*. Dimitrov et al. (2015) therefore argue that CRAs issue lower, less accurate and less informative ratings following the DFA, especially in circumstances where their reputational costs are greater.

Based on a survey of CRAs, investors and regulators, EC (2016) analyses the key points of the EU CRA regulation (see Section 2.3.2) and assesses its impact. The study argues that the requirement for CRAs to publish historical performance and rating information may increase reputational costs for CRAs and provide investors with the information necessary to evaluate rating quality. However, the study also suggests that evaluating the historical performance is a complex task that only sophisticated investors can undertake. Much of the literature that examined the regulatory impact on bank ratings restricts itself to the sovereign-bank rating channel (Huang and Shen, 2015; Klusak et al., 2017, see Section 2.3.4) and neglects to analyse how the regulation directly impacts the bank rating market.

To summarize, previous related studies have focused on the impact of US regulatory reforms on corporate ratings and structured finance ratings. There is a significant void in the literature

[80] Behr et al. (2018) examine the introduction of the US SEC regulations in 1975, and show that this boosted CRAs' market power by increasing barriers to entry and regulatory reliance on credit ratings, leading to rating inflation.

regarding both the impact of the regulatory changes on the FI rating segment and in the European setting.

3.3 DATA

FIs' ratings are suitable for investigating the research questions, because they were not the driving factor behind many of the regulatory changes. The earlier regulatory changes in the EU were typically aimed at CRAs rating structured finance products (although the changes also apply to other rating segments) which played a large role in the 2007-2008 sub-prime crisis. The later changes in the EU (CRA III) are driven by conflicts and issues that arose in the EU sovereign debt crisis, primarily caused by concerns relating to sovereign ratings.

The original EU dataset consisting of 2,503 rated FIs from the 27 EU countries. FI ratings and accounting variables are obtained from BankScope. [81] Additional rating information is sourced from CRA publications. After Volkbanks[82] have been eliminated, the sample consists of 758 rated FIs in 27 EU countries, of which 378 are rated by S&P, 468 by Moody's and 494 by Fitch (see Table 3.1), during the period from 1st January 2006 to 1st June 2016. Annual financial variables are used in order to maximise data coverage in the sample and only FIs that are rated and have financial characteristics available during the sample period are included. FIs may enter or exit the sample throughout the sample period to avoid any potential "survivor bias".

A panel dataset is constructed at monthly frequency (as in Caporale et al., 2012; Chen et al., 2016 and others), with the daily rating data, and annual financial characteristics, mapped onto it. The correlation matrix (see Figure 3.1) shows no strong correlation among the control variables. Table 3.2 presents the descriptions and summary statistics for the variables, which are selected following the literature on the determinants of FI ratings (e.g. Huang and Shen, 2015).

The distribution of non-interest income to gross revenue (%) for FIs in the sample is shown in Figure 3.2. This ratio indicates what proportion of the FI's business is in more traditional interest taking business such as loans and what comes from alternative business such as fee-

[81] The sample of FIs are what BankScope classifies to be "banks" that were active at some point during the sample period.

[82] Scattered throughout Europe are many small "village" banks that often share a credit rating. As such they do not behave as individuals in the sample but rather as a single entity (or small groups), it is therefore necessary to remove them to avoid bias in the sample. The majority of these FIs are independent local Volkbanken in Germany and Austria (over 1000), that are sometimes also known as VB or VR banks. All the FIs containing the name Volksbank (or Volks, which pertain to Volksbanken and Raiffeisenbanken), Raiffeisen, Sparkasse, VB or VR are removed from the sample. Some of these FIs are also present in France where they are known as "Caisse regionale" or "Banque populaire" and are also excluded. It is also possible to identify Volksbanks by the date of their rating changes, as they all change ratings on the same date and by the same amount.

based activity. The figure shows a normal distribution of FIs centred on a ratio of approximately 0.3, meaning that on average the FIs in the sample get 30% of their revenue from non-interest income, i.e. not from traditional loan making activities. Examining the distribution of FIs, there are not “two types” of FIs i.e. investment vs traditional banks. But rather a mix of FIs that undertake both traditional loan-making and non-traditional fee-based activities to varying degrees. There are very few FIs in the sample that are almost entirely “traditional” or “non-traditional” banks, the majority have a mixed business model.

The credit ratings are mapped to a 52-point comprehensive credit rating (CCR) scale: AAA/Aaa = 52, AA+/Aa1 = 49, AA/Aa2 = 46 …, CCC+/Caa1, CCC/Caa2, CCC-/Caa3 = 4, C/SD/CC/D = 1.[83,84] Then, for positive (negative) watch +2 (-2) is added and for positive (negative) outlook +1 (-1) is added.[85] The distribution of ratings in the sample is shown in Figure 3.3 (and broken down in Panel B of Table A. 3.1 in the Appendix). The figures show that S&P/Fitch issue slightly higher ratings (peaks at A+) than Moody’s (peaks at A2) and that the sample is well distributed with many ratings in each category.

There are 1,108 negative rating, outlook and watch events and 430 positive events (see Table 3.3 and Table A. 3.3). S&P issues more downgrades during the sample period (398), than Moody’s (379) and Fitch (331). Moody’s issues the most upgrades (191), compared to S&P (142) and Fitch (97). There is a spike in the number of rating downgrades during 2011 and 2012 around the time of the EU sovereign debt crisis and a secondary smaller spike in 2008 and 2009 following the 2008 financial crisis.

Control variables are included to reduce the time varying heterogeneity in the FIs and to account for variation in FIs characteristics that could be driving changes in their ratings. Seven control variables are utilized: asset quality, management efficiency, profitability, revenues, leverage, liquidity and size. Many of these are also employed by other studies in the literature to determine FI ratings (Huang and Shen, 2015; Hau et al., 2013; Shen et al., 2012). Table A. 3.6 reports the control variables included in the model and the papers that employ them to model FI ratings.

[83] Unlike S&P and Moody’s, Fitch does not differentiate between ratings at the CCC/Caa level since 2006.

[84] Eq. (3.1) to (3.3), produced equivalent results (see Table A. 3.2 in the Appendix) when using the 18-notch rating scale (which excludes outlook and watch signals) as used by Becker and Milbourn (2011) and Dimitrov et al. (2015). See Section 3.5.4.

[85] The 52-point and 18-notch rating scales are presented in Panel A of Table A. 3.1 in the Appendix. The frequency of the occurrences of each rating is presented in Panel B of Table A. 3.1.

Asset Quality is measured as the ratio of loan-loss provisions to net interest revenue. Poon and Firth (2005) state that their results indicate that asset quality is an important factor in determining FI ratings.

Management Efficiency is the ratio of cost to income. Shen et al. (2012) argue that FIs with a lower management efficiency display better ratings. *Profitability* is measured as the return on assets and numerous papers (Huang and Shen, 2015; Poon and Firth, 2005; Shen et al., 2012) show a significant relationship between FI profitability and credit rating. Typically, FIs with higher profitability have higher ratings, as those FIs who make a greater profit are less likely to default than a FIs that are losing money.

Revenues is defined as non-interest income over gross revenues and describes what business activities the FI is undertaking. More traditional FIs with a greater proportion of loan taking will have a lower ratio compared to those FIs heavily invested in fee-based activities. *Leverage* is defined as total assets to equity. A FI with more leverage is better able to deal with significant losses.

Liquidity is defined as the ratio of liquid assets to deposits and short-term funding. A FI that holds a greater proportion of liquid assets is better able to cope with unexpected financial shocks. FIs that hold more liquid assets and have a larger deposit base generally have higher returns (Berger and Bouwman, 2013). Poon and Firth (2005) suggest that liquidity is an important factor in determining FI ratings. While Shen et al. (2012) find a positive relationship between FI liquidity and FI ratings. Distressed FIs faced severe liquidity issues and Acharya and Mora (2015) observe that failed, or nearly failed, FIs fight for retail deposits by offering higher deposit rates. These combined with the common occurrence of both liquidity and credit risk, may act to push FIs into default.

Size is defined as the natural log of the FIs assets. Larger FIs have a tendency to receive higher credit ratings and metrics of size provide some of the strongest correlations with credit rating levels (Huang and Shen, 2015; Pettit et al., 2004). It is also noted that metric of size also reflects other defining factors such as geographic and product market diversification, bargaining power, competitiveness, brand stature and market share. Poon and Firth (2005) and Shen et al. (2012) find positive relationships between FI size and rating. Hau et al. (2013) note that larger FIs tend to have increased revenue diversification and therefore increased stability and they find a positive relation between FI size and rating.

The control variable data is trimmed to remove outliers, with the bottom and top 0.5% is trimmed from ROAA and Equity to total assets, while the top and bottom 1% is trimmed from Cost to income ratio, Loan loss provisions to net interest revenue, Non-interest income to gross revenues and Liquid assets to deposits and short-term funding. Total assets did not require trimming.

3.3.1 FALSE WARNINGS

A warning is defined as a period in which a FI is rated BB+ or below (as in Dimitrov et al., 2015).[86] A false warning is then defined as a warning for a FI that does not default in the following 12 months. 12-months period is the length of time used by Dimitrov et al. (2015). Warnings using B+ and below and a period of 24 months are estimated as robustness tests, and the results are consistent (see Section 3.5.4, Table A. 3.5). It is possible for a FI to receive both false and true warnings in separate time periods, e.g. if the warning is issued too early.

One limitation of the method is the lack of occurrences of false warnings, or even warnings, in the sample. The sample consists of 758 FIs, of which only 87 had warnings over the sample period. Out of the 87 FIs with warnings issued, 80 at some point incurred a false warning. Throughout the sample S&P, Moody's and Fitch issue false warnings to 31, 62 and 53 FIs respectively (a more detailed breakdown is show in Table A. 3.4). The incidence of false warnings throughout the sample period is shown in Figure 3.4 and can be seen that the incidence of false warnings increases from 2010 to 2015.

The process to create the sample is as follows. Firstly, all the warnings (ratings falling to or below BB+)[87] are identified in the sample. Information on the FIs is gathered from Bankscope, Bloomberg, S&P's CapitalIQ and Kerlin et al. (2016),[88] as well as the ratings themselves. Actual FI failures are rare in Europe and therefore defining when a FI faces distress can be challenging. Betz et al.'s (2014) method is adopted here, whereby FIs with warnings are examined for potential distress events, which include: (i) default/liquidation, (ii) government intervention/support and (iii) forced merger. The distress events are defined as follow: A *bankruptcy* occurs when the net worth of the FI falls below the country specific guidelines. A *liquidation* occurs when the FI is sold following the guidelines of the liquidator in which case

[86] There are usually multiple instances for each FI, as a FI may hold a low rating for many months or years.
[87] 8 points on the 18-notch scale
[88] Some of these FIs also appeared in the paper Ayadi and Thyri (2015), whereby they are double checked.

the shareholders may not receive full payment for their ownership. There are two kinds of *defaults* defined: (i) default as a result of failing to pay interest or principal on at least one financial obligation beyond any grace period specified by the terms, and (ii) a FI completes a distressed exchange, where at least one financial obligation is repurchased or replaced by other instruments with a diminished total value.[89]

Secondly, data on FIs receiving state support and intervention is employed. A FI is defined to be in distress if it receives a capital injection from the state or enrols in an asset relief programme, such as asset guarantees or protection. Events are defined to last from the announcement of state support up to the end of the execution of the support programme. Being owned by the state (nationalized) is defined as receiving state aid and as such is a distress event.

Lastly, mergers when a FI is in distress encapsulate the private sector solution to FI distress. Following Betz et al. (2014) definition, the merged entities are defined to be distressed if (i) a parent received state aid within the 12 months following the merger, or (ii) the merged entity has a coverage ratio below zero in the 12 months prior to the merger.[90] The reason for using the coverage ratio is so that only mergers that are forced due to stress are captured. The coverage ratio's definition follows that used by Betz et al. (2014) and is defined as the ratio of capital equity and loan reserves minus non-performing loans to total assets.

In many cases where the FI may be likely to default (i.e. rated at or below BB+), its rating is withdrawn before possibly defaulting. On further investigation of S&P, Moody's and Fitch's withdrawal policies, it appears that they have several common points, primarily that they will try to avoid revoking a rating prior to an imminent rating change and that they will publish a statement when the rating is removed.[91] Thus, each withdrawal is examined individually, and the institution investigated for possible distress.

[89] There is also the condition that if a FI has a default rating then the warning is not false.

[90] The coverage ratio is widely used to define destressed FIs (Betz et al., 2014; Gonzalez-Hermosillo, 1999).

[91] Moody's typically may withdraw ratings for a number of reasons (Moody's, 2011), which include; (i) Bankruptcy/Liquidation/Debt-Restructuring/Write-down, (ii) Incorrect, insufficient or otherwise inadequate information, (iii) reorganization, (iv) maturity of obligation or termination of program, (v) business reasons, (vi) clerical error and (vii) conflicts of interest. Chief of interest to this study is withdrawal due to bankruptcy, fortunately Moody's typically issues a statement regarding the reason for withdrawing the rating.
S&P state in their policy documents (S&P, 2016) that they may "withdraw or suspend a credit rating at any time" with their "sole discretion". They do state however, that "under no circumstances will an issuer's request to withdraw a credit rating avoid an imminent rating change", however this does not extend to S&P discretion. S&P will, like Moody's, publish a statement when withdrawing or suspending a rating.
Fitch state that they may withdraw a rating for several reasons, similar to S&P's, that include the entity ceasing to exist due to merger or bankruptcy, insufficient information (potentially due to a lack of cooperation with the

3.3.2 STOCK MARKET DATA

Stock market data for 107 listed FIs and their respective country stock indices is collected (for the list of indices, see Table A. 3.7 in the Appendix) for the period 1st January 2006 to 1st June 2016 from DataStream. The summary statistics are shown in Table A. 3.8 in the Appendix, where there are 443,641 observations used over the period 1st January 2006 to 1st June 2016 and 1,538 rating events (including outlook and watch) and 925 (excluding outlook and watch). The abnormal stock returns are then calculated for each day using Eq. (3.6) and a 200-day event window (see Section 3.4.3).

The breakdown of rating announcements by S&P, Moody's and Fitch is reported in Table 3.3 (and in more details in Table A. 3.3), along with the number of rating, outlook and watch rating upgrades and downgrades. It should be noted that during the sample there is significantly more downgrades than upgrades issued by all three CRAs. S&P issues the highest number of downgrades during the sample (398), while Fitch issues the lowest (331), Moody's issues the highest number of upgrades (191) while Fitch again issues the lowest (97). Of the negative credit signals, 66% involved a rating category change, while 45% of positive credit signals involved a rating category change (see Table 3.3). Most rating changes are at 1-CCR (outlook), 2-CCR (watch) and 3-CCR (one-notch) points. But there are cases of downgrades by greater than 9-CCR (greater than 3-notch). To account for the clustering of rating events, in addition to the whole sample both intendent and clustered events are considered separately as robustness test (see Section 3.5.4).

3.3.3 S&P MARKET SHARE

To distinguish between markets with greater and lesser reputational concerns, it is necessary to utilize a proxy. A suitable proxy is based on Becker and Milbourn (2011) and Dimitrov et al. (2015) but is adapted to the European FIs' context. Two CRAs with dominant market share will consider a strengthening presence of a third CRA with a smaller market share as a threat. Consequently, they will behave increasingly competitively (caring less about their reputation and being more likely to inflate ratings) in seeking to stave off continued incursion into the market by their competitor.

agency) or being delisted from the stock exchange. They do, as with the other two CRAs, publish an announcement with the level of the rating at withdrawal and the reason for withdrawal. Fitch also note that withdrawals cannot be used to forestall a rating action.

Becker and Milbourn (2011) and Dimitrov et al. (2015) chose Fitch market share as a proxy for reputational concerns in the US corporate rating market, because Fitch has a relatively weaker presence in that market. This Chapter's sample consists of European FI ratings, where the three large CRAs have substantially varying market shares across countries. Fitch is a relatively stronger participant in Europe than in the US and stronger in the banking sector rather than in corporate bond ratings. The long-established strength of Fitch in the European FI rating sector is influenced by: (i) having their global headquarters in London; (ii) historical acquisitions of IBCA Limited (thereby achieving a strong European presence) and Thomson Financial BankWatch (thereby strengthening their position in FI ratings). Calculated at the issuer level, S&P has the lowest market share in the European FI rating market and thus its market share serves better as a proxy for reputational concerns. Further, S&P has the lowest rate of growth of market share in FI ratings during the sample period, while Fitch has the fastest rate (see Figure 3.5).[92]

Bae et al. (2015) argue that there are two problems with the measure used by Becker and Milbourn (2011) and Dimitrov et al. (2015). First, that the results are driven by an endogeneity problem caused by unobservable industry effects and second that the positive relation between credit ratings and Fitch market share does not hold when only firms in non-regulated industries are included in the analysis. This Chapter addresses the first issue by limiting the sample to a single industry and calculating market share variation on the country level, while controlling for country level variation using country*year fixed effects as well as FIs characteristics. The second issue is addressed by considering a single industry, whereby the regulation is therefore applied homogenously across the sample (as all countries are affected equally and simultaneously by the regulation). The Chapter further checks, using Eq. (3.1), that S&P market share has a positive relation to rating levels in just the post regulatory period, in addition to the entire sample (see Panel D of Table A. 3.9 in the Appendix).

S&P market share is calculated by dividing the number of S&P issuer ratings (assigned to FIs) in country *j* in year *t* by the total number of FI issuer ratings assigned by the big three CRAs in

[92] Also, when Fitch market share used in Eq. (3.1), there is no positive correlation with European FI rating levels (results are available upon request). Hence, Fitch market share would not act as a good proxy for reputation as there is no positive relationship with rating levels and therefore competition. CRAs have increased reputational concerns in markets where there is less competition (Becker and Milbourn, 2011; Dimitrov et al., 2015). As S&P has the smallest market share, its increased presence in the market triggers increased competitive behaviour from the other two incumbent CRAs. As Fitch has a more established presence, increased market share does not trigger more competitive behaviour from the other two CRAs.

country *j* in year *t* (the resulting market share is lagged by 1 year in estimated models). Figure 3.6 and Figure 3.7 show that the average S&P market share varies sufficiently across all countries in the sample and across time. S&P market share ranges from an average of 21.40% in 2005 to 24.08% in 2016. S&P market share also varies across countries with Estonia having no S&P FI ratings and Luxembourg having an average S&P market share of 40.12%. It is then necessary to confirm that S&P market share (***S&PMS***) can be used as a proxy for reputational concerns. The inference is that Moody's and Fitch assign higher ratings in countries with higher S&P market share. The following ordered logit model[93] is estimated:

$$\mathrm{CR}_{i,j,k,t} = \beta_1 \mathrm{S\&PMS}_{t-1} + \beta_2 \mathrm{BANK}_{i,j,k,t-1} + \beta_3 \mathrm{Moody's}_t + \beta_4 \mathrm{Fitch}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t} \qquad (3.1)$$

$\boldsymbol{CR_{i,j,k,t}}$, is the rating of FI *i* in country *j* by CRA *k* at time *t* based on the 52-point CCR scale. $\boldsymbol{S\&PMS_{t-1}}$ is S&P market share (lagged by 1 year), defined as a dummy variable with a value 1 for FIs in countries within the lower quartile of S&P market share and zero within the upper three quartiles of S&P market share.[94] ***BANK*** is a set of FI control variables, including asset quality, efficiency, profitability, revenues, leverage, liquidity and size (see Table 4.2), ***Moody's*** and ***Fitch*** are dummy variables that distinguish between ratings assigned by Moody's, Fitch and S&P (both dummies are zero for ratings assigned by the latter).

CF*YF is a full set of interacted country (***CF***) and year (***YF***) dummy variables. The use of interacting fixed effects is an increasingly common practice (e.g. Jiménez et al., 2012), as the approach allows for the control of possible omitted variable bias which can result in endogeneity issues (see Section 3.4.1). The interaction term takes account of any variation present across different times and countries, and controls for differences in the macroeconomic conditions of the countries. The results (see Panel C of Table A. 3.9) of Eq. (3.1) are robust to using no fixed effects.

The results of Eq. (3.1) are presented in Table 3.4 and are consistent with the expectation that Moody's and Fitch issue lower ratings in countries in the lower 25th percentile of S&P market share (with $\boldsymbol{S\&PMS_{t-1}}$ being negative and significant). This confirms that Moody's and Fitch are less concerned with their reputation and thus more likely to inflate their FI ratings in countries with higher S&P market share.

[93] The results of Eq. (3.1) is robust to using ordered probit estimations (see Panel B of Table A. 3.9).
[94] The results of Eq. (3.1) are also robust to using both 10th and 40th percentiles of S&P market share in the $\boldsymbol{S\&PMS_{t-1}}$ dummy, and also to using the percentage market share in each country. See Panel A and E of Table A. 3.9.

3.4 METHODOLOGY AND HYPOTHESES

This Section discusses the methods of examining the impact of the EU regulatory reforms on the quality of ratings. Three hypotheses are tested, namely the *disciplining*, *conservatism* and *reputation* hypotheses. The Section composes of three sub-sections. Section 3.4.1 examines rating levels, Section 3.4.2 investigates false warnings, and Section 3.4.3 analyses the informational content of ratings.

3.4.1 RATING LEVELS

A key aim of the EU regulation is to reduce rating inflation. The Chapter first examines whether rating levels decreased in the post regulatory period, as would be predicted by the *disciplining hypothesis* (improvements in CRA methodology and increased risk of regulatory penalties cause a reduction in rating inflation), *rating conservatism* (CRAs under-rate issuers to avoid falling foul of the increased regulatory stringency and liability) and *reputation hypothesis* (CRAs assign lower ratings in order to safeguard their reputation). To test this, the following ordered logit model is estimated:

$$\mathrm{CR}_{i,j,k,t} = \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{BANK}_{i,j,k,t-1} + \beta_3 \mathrm{Moody's}_t + \beta_4 \mathrm{Fitch}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t} \quad (3.2)$$

$CR_{i,j,k,t}$ is the credit rating of FI *i* in country *j* by CRA *k* at time *t* based on a 52-point CCR scale (see Section 3.3). ***Post*** is a dummy variable that takes the value of one after the new regulation and zero before. Eq. (3.2) is estimated three times using different dates for the start of the post regulatory period, first using the 16th September 2009, enacting the first wave of reforms (CRA I), secondly using 1st July 2011, when the regulation became more strongly enforced by the newly established ESMA (CRA II), as the start of the post-regulatory period. Lastly, Eq. (3.2) is estimated using two separate post-regulatory dummies. ***Post1*** takes the value one during the period July 2011 to May 2013, and zero otherwise. ***Post2*** takes the value of one after May 2013 and zero otherwise to capture the latter regulatory update that increased the stringency of the rules and introduced a new liability regime. ***BANK*** is a set of variables that control for FI specific characteristics (see Table 3.2). ***Moody's*** and ***Fitch*** are dummy variables that distinguish between ratings assigned by Moody's, Fitch and S&P (both dummies are zero in the latter case). ***CF *YF*** is a full set of interacted country and year dummy variables.

To account for unobserved variation in economic development, the industrialisation level or geographical bias relating to the countries, the model includes country * year dummy variables. The use of interacting fixed effects is becoming an increasingly common practice (Klusak et al., 2017; Jiménez et al., 2012), as the approach allows for the control of possible omitted variable bias which can result in endogeneity issues. By this method the identification of macroeconomic conditions comes purely from the interactions, following Jiménez et al. (2012); Klusak et al. (2017); Thompson (2011). The use of fixed effects requires that one drops the macroeconomic variables from the regression as they become collinear with the dummy variables. In line with Acharya et al. (2013) and Philippon and Reshef (2013), the Chapter uses country and time interacted fixed effects, along with a time dummy for regulatory change. The results are consistent when using separate country and time fixed effects (see Table A. 3.11) and when using no country or year fixed effects (see Table A. 3.12, see Section 3.5.4) (as done by Dimitrov et al., 2015).[95]

The *reputation hypothesis* makes a key different prediction to the other two hypotheses, namely that the effect should be stronger in countries where CRAs care more about their reputation. To detect the presence of reputational effects, the model is expanded to consider whether the FI is in a country with stronger or weaker reputational concerns. The Chapter uses S&P market share as a proxy for reputational concerns (see Section 3.1). In countries with a greater presence of the third CRA, the other two CRAs care less about their reputation due to the stronger competition (Becker and Milbourn, 2011; Dimitrov et al., 2015). Conversely, countries with a lower S&P market share are characterised by greater reputational concerns for Moody's and Fitch, therefore reputational effects should be stronger. If a stronger decrease in rating levels is observed in countries with greater reputational concerns, this indicates the presence of reputational effects. If no difference between countries with differing reputational concerns is observed, this implies that either the *disciplining hypothesis* or *rating conservatism* is more relevant to any decrease in rating levels. The following ordered logit model is estimated:

$$\begin{aligned}\mathrm{CR}_{i,j,k,t} = {} & \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{S\&PMS}_{j,t-1} + \beta_3 \mathrm{Post} * \mathrm{S\&PMS}_{i,j,t-1} + \beta_4 \mathrm{BANK}_{i,j,k,t-1} \\ & + \beta_5 \mathrm{Moody's}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t}\end{aligned} \tag{3.3}$$

The sample is split into two sub groups, the lower quartile of S&PMS and the upper three quartiles of S&PMS. The variable ***S&PMS$_{j,t}$*** is a dummy variable with a value of one if in the

[95] In all the regressions, because a single firm can have multiple rating announcements in the sample, standard errors are clustered on a firm level (as in Dimitrov et al., 2015).

first group and zero if in the second. The addition of the interaction ***Post*S&PMS*** allows for the extraction of the effect due to variations in reputational concerns in the post regulatory period and thus ***Post*** represents the change arising solely from the regulation.

3.4.2 FALSE WARNINGS

This Section explores whether lower credit ratings in the post regulatory period are warranted by changing FI creditworthiness. If any change in rating levels is fully justified, there will be no significant increase in false warnings. If the observed lower ratings are not fully justified, an increase in false warnings would be identified (i.e. unjustified downgrades). The following logit model of false warnings is estimated:

$$\mathrm{FW}_{i,j,k,t} = \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{BANK}_{i,j,k,t-1} + \beta_3 \mathrm{Moody's}_t + \beta_4 \mathrm{Fitch}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t} \quad (3.4)$$

$\boldsymbol{FW_{i,j,k,t}}$ is a dummy variable with a value of one for a FI *i* rated BB+ or lower in country *j* by CRA *k* at time *t* that does not face financial distress within one year and zero otherwise (see Section 3.3.1 and Dimitrov et al. (2015)).[96]

The three hypotheses make different predictions with regards to false warnings. The *disciplining hypothesis* predicts no increase in the number of false warnings, because the regulation has acted to improve rating methodology and reduce rating inflation. *Rating conservatism* predicts an increase in the number of false warnings, as greater risk of regulatory intervention causes CRAs to under-rate, thereby inducing an increased incidence of unwarranted downgrades. The *reputation hypothesis* predicts that any increase in false warnings is more apparent in countries with stronger reputational concerns in the post-regulation period, as CRAs seek to protect their reputation. The following model is estimated:

$$\begin{aligned} \mathrm{FW}_{i,j,k,t} = {} & \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{S\&PMS}_{j,t-1} + \beta_3 \mathrm{Post} * \mathrm{S\&PMS}_{i,j,t-1} + \beta_4 \mathrm{BANK}_{i,j,k,t-1} \\ & + \beta_5 \mathrm{Moody's}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t} \end{aligned} \quad (3.5)$$

[96] The results of Eq. (3.4) and Eq. (3.5) are robust to using a rating of B+ and below as the cut off point for a warning instead of the original cut off point of BB+ (see Table A. 3.5). The results are also robust to changing the length of time to observe financial distress from one year to two years (see Table A. 3.5). See Section 3.5.4.

A positive and significant coefficient on ***Post*** would indicate an increase in false warnings and unwarranted downgrades in the post-regulatory era. ***Post*S&PMS*** captures the difference in impact between countries with stronger and weaker reputational concerns.

3.4.3 INFORMATIONAL CONTENT OF RATINGS

ESMA seeks to reduce the mechanistic reliance on credit ratings and hence to reduce market overreactions to downgrades, which should consequently reduce the market reaction to negative rating signals. Improving rating quality would increase the informational content of (hence greater market reaction to) positive rating news. The market reaction to a rating event on day *t* is measured by the abnormal stock return, calculated using a technique widely adopted in the literature (e.g. Correa et al. 2014; Behr and Güttler 2008):

$$Abnormal\ Return = Stock\ Return - \alpha - \beta * Market\ Return \tag{3.6}$$

The FI stock return is calculated over a 2-day period (*t-1*, *t+1*). α and β are the intercept and slope coefficients, respectively, of an OLS regression of FI *i*'s stock returns on the market return estimated using daily data from an event window of 230 days prior to 30 days prior [-230, -30] each rating announcement and a constant.[97]

An OLS model of rating announcements with country and year interacted fixed effects is constructed (positive and negative credit rating events are considered separately) as follows:

$$\begin{aligned}\mathrm{AR}_{i,j,k,t} = {} & \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{Rating\ Event}_{i,j,k,t} + \beta_3 \mathrm{Post}_t * \mathrm{Rating\ Event}_{i,j,k,t} \\ & + \beta_4 \mathrm{BANK}_{i,j,k,t-1} + \beta_5 \mathrm{Moody's}_t + \beta_6 \mathrm{Fitch}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t}\end{aligned} \tag{3.7}$$

Rating Event$_{it}$ is a dummy variable equal to 1 on a credit rating event date *t* for FI *i* and zero otherwise. ***AR*** is the abnormal stock return and is calculated as in Eq. (3.6).

The *disciplining hypothesis* predicts that rating downgrades and upgrades will become more informative, as improved methodologies, reduction in rating inflation and greater diligence by CRAs will result in improved rating quality. *Rating conservatism* predicts that downgrades will become less informative, because CRAs tend to deflate their ratings to protect themselves against increased regulatory intervention. In addition, the EU regulation aims to mitigate the

[97] Stock market data for 107 listed FIs and their respective country indexes is collected from DataStream (see Section 3.3.2).

mechanistic market reaction to rating downgrades, which may potentially reduce the stock price reactions to negative rating events. Conversely, rating upgrades may become more informative, as over-rating exposes CRAs to greater potential penalties and liability, which incentivises CRAs to expend greater effort to ensure that each upgrade is warranted. The *reputation hypothesis* stipulates that rating downgrades may become less informative as CRAs issue downgrades partly to protect their reputation. Conversely, rating upgrades may become more informative because CRAs wish to avoid the perception of biased ratings and therefore expend greater effort when issuing rating upgrades. Any effect due to the *reputation hypothesis* would differ between countries with greater and lesser reputational concerns.

The Chapter also estimates Eq. (3.8), whereby the interaction term ***Post*Rating Event********S&PMS*** is the additional effect that FI rating events have in countries in the bottom quartile of S&P market share (greater reputational concerns):

$$\begin{aligned}\mathrm{AR}_{i,j,k,t} = {} & \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{Rating\ Event}_{i,j,k,t} + \beta_3 \mathrm{Post}_t * \mathrm{Rating\ Event}_{i,j,k,t} \\ & + \beta_4 \mathrm{S\&PMS}_{i,t-1} + \beta_5 \mathrm{Rating\ Event}_{i,j,k,t} * \mathrm{S\&PMS}_{i,t-1} + \beta_6 \mathrm{Post}_{i,t} \\ & * \mathrm{S\&PMS}_{i,t-1} + \beta_7 \mathrm{Post}_{i,t} * \mathrm{Rating\ Event}_{i,j,k,t} * \mathrm{S\&PMS}_{i,t-1} \\ & + \beta_8 \mathrm{BANK}_{i,j,k,t-1} + \beta_9 \mathrm{Moody's}_t + \beta_{10} \mathrm{Fitch}_t + \lambda \mathrm{CF} * \mathrm{YF} + \varepsilon_{i,j,k,t}\end{aligned} \tag{3.8}$$

3.4.4 SUMMARY

The three hypotheses' predictions on rating levels, false warnings and the informational content of rating upgrades and downgrades are summarized below:

Hypotheses

Hypothesis	Rating Levels	False Warnings	Upgrades	Downgrades
Disciplining	Decrease	No change	More informative	More informative
Rating conservatism	Decrease	Increase	Potentially more informative	Less informative
Reputation	Decrease – varies with	Increase in countries with greater	Potentially more informative –	Less informative – varies with

	reputation concerns	reputation concerns	varies with reputation concerns	reputation concerns

3.5 EMPIRICAL RESULTS

3.5.1 RATING LEVELS

This Section analyses whether rating levels have changed following the introduction of the EU regulation of CRAs. To preview the findings, this Section shows that: (i) rating levels are lower following the regulation, (ii) lingering reputational effects from the reputational shock of the financial crisis dissipate and the effect does not differ with reputational concerns, and (iii) the May 2013 regulation update strengthens the regulatory/conservatism effect.

Firstly, Eq. (3.2) is estimated using September 2009 as the start of the post-regulatory period, with the results reported in Table 3.5.[98] The coefficient of the regulatory change ***Post*** is -0.179*** and thus the odds that a FI is rated as non-investment grade are 1.20 ($1/e^{-0.179}$) times greater following the passage of the regulation.[99] Secondly, Eq. (3.2) is estimated using the regulatory start date of July 2011 (establishment of ESMA), with the results reported in Table 3.5. The effect of regulation is stronger, with the ***Post*** coefficient is -0.304*** (the odds that a FI is rated as non-investment grade are 1.36 times greater following the CRA regulatory reforms). The results are consistent with the *disciplining hypothesis*, whereby rating quality improves and there is a reduction in inflated ratings, and with *rating conservatism*, whereby CRAs are induced by greater regulatory scrutiny to issue more conservatively biased ratings. The results are also in line with the *reputation hypothesis*, whereby CRAs issue lower ratings following a reputational shock in order to protect their reputation.

Eq. (3.2) is then estimated using two separate post-regulatory dummies. ***Post1*** takes the value one during the period July 2011 to May 2013, and zero otherwise, to capture any effects caused by the enforcement of the initial regulation by ESMA. ***Post2*** takes the value of one after May 2013 and zero otherwise to capture the latter regulatory update, the results reported in Table 3.5. Eq. (3.2) produces the same inferences as reported above for the July 2011 handover of responsibilities to ESMA. The regulatory update in May 2013 acts to strengthen this effect with a further decrease (***Post2*** coefficient is -0.413 and the odds of being rated non-investment grade

[98] The results of Eq. (3.2) and (3.3) are also robust when estimated using the 18-notch rating scale, see Table A. 3.2 and Section 3.5.4. Eq. (3.2) and (3.3) is also estimated using the ordered probit or OLS modelling approaches, and results are also consistent, see Table A. 3.10 and Section 3.5.4.

[99] The proportional odds ratio in ordered logit captures the proportional change in the odds that a FI is rated below a certain credit rating level, such as BBB-/Baa3, for a unit change in a predictor variable, holding other variables in the model constant (see UCLA: Statistical Consulting Group, 2017; Dimitrov et al, 2015). The odds of being below a given level (e.g. B-) are multiplied by e^{β}, where β is the coefficient on the variable.

are 1.51 times greater). Consistent with the *rating conservatism* hypothesis, this additional decrease could arise from the increased stringency of the rules introduced by the 2013 regulatory update. This primarily introduced a new liability regime (Article 35a), giving investors and issuers the right to sue for damages, and strengthening existing disclosure and transparency requirements.

To investigate the difference further, Eq. (3.3) is estimated to take account of differences between countries with different reputational concerns, with the results also reported in Table 3.5. Rating signals are restricted to those of Moody's and Fitch and the estimated model includes the S&P market share variable. Again, the impact of the regulation is observed in all countries following September 2009, July 2011 and May 2013,[100] implying the strong presence of either *disciplining* effects or increased *rating conservatism*.

Using the September 2009 start date, there is a strengthening of the effect in the bottom quartile of S&P market share, where reputational effects are magnified. FIs in these countries experience a significantly greater decrease in rating levels, with the interaction of ***Post*S&PMS*** is significant (-0.195**, this implies that the odds that a FI is rated as non-investment-grade is 1.47 greater after the passage of the regulation in countries with stronger reputational concerns, compared to 1.21 greater odds in countries with lesser reputational concerns).[101] The results indicate the presence of reputational effects when the regulation was introduced in September 2009, it is likely that these effects are due to the reputational shock of the 2008 financial crisis that heightened reputational concerns for CRAs (Bedendo et al., 2018). The evidence for this is supported by the negligible presence of reputational effects when using the July 2011 regulatory start data, as there is no variation in effect between countries with greater or lesser reputational concerns (insignificant ***Post*S&PMS***) and countries in the bottom quartile of S&P market share reveal no differences compared with countries in the top three quartiles. This continues to be the case when the May 2013 regulatory update is considered, as ***Post1 * S&PMS*** and ***Post2 * S&PMS*** coefficients are not significant, indicating that there is no difference in the impact of the regulation between countries where CRAs have stronger or weaker reputational concerns.

The evidence is that the regulation acts through either the discipline channel or by stimulating increased *rating conservatism*, supporting the regulators' views in EC (2016). This finding

[100] ***Post, Post1*** and ***Post2*** are all negative and significant (see Table 3.5).
[101] Obtained by adding ***Post*S&PMS*** to ***Post***, i.e. $e^{0.188+0.195} = e^{0.383} = 1.47$.

contrasts strongly with US evidence that reputational effects are strongly connected to the reductions in corporate ratings levels.[102] Having ascertained that the regulation appears to be acting primarily through *disciplining hypothesis* or increased *rating conservatism*, Section 3.5.2 will seek to determine which of the two is the dominant hypothesis.

3.5.2 FALSE WARNINGS

This Section determines whether *disciplining hypothesis* or *rating conservatism* is driving the decrease in rating levels. To preview the findings, this Section shows: (i) an increase in false warnings in the post regulatory period, (ii) the increase does not differ with reputational concerns, and (iii) the May 2013 regulation update strengthens the effect.

The results of Eq. (3.4) are reported in Table 3.6.[103] Following September 2009, no increase in false warnings is observed (***Post*** is insignificant). The implies that the initial fall in rating levels is warranted by CRAs updating their rating practices, methodologies and improving rating quality. After July 2011, there is a significant increase in false warnings (***Post*** coefficient is 0.383*** and the odds that a CRA would issue a false warning after July 2011 are 1.47 ($e^{0.383}$) times greater than before the CRA regulation). This increase in false warnings implies that not all rating downgrades are warranted. There are two potential reasons for this. First, increased *rating conservatism* caused by greater regulatory intervention in cases of over-rating an issuer (especially as ESMA now effectively enforces the regulation). Second, CRAs issue more downgrades to protect their reputation and build reputational capital.

Eq. (3.4) is also estimated using two separate post-regulatory dummies. The results show a strengthening of the result from ***Post1*** to ***Post2*** (the coefficient is 0.694***, which doubles the odds of a false warning). This increase in unwarranted downgrades following the strengthening of the regulation in May 2013 and the introduction of the civil liability regime is highly suggestive of an increase in *rating conservatism* by CRAs as they respond to the increased potential cost for over-rating.

---

[102] Dimitrov et al. (2015) find evidence of the presence of reputational effects causing a significant decrease in corporate rating levels in the post Dodd-Frank era in the US. This effect is stronger in industries with greater reputational effects. They find no significant decrease in industries with lesser reputational effects. They find no evidence that the Dodd-Frank legislation acts through the discipline channel.

[103] Eq. (3.4) and (3.5) are also estimated using the probit or OLS models, and the results are robust (see Table A. 3.10 and Section 3.5.4).

To differentiate between the two possibilities, Eq. (3.5) is estimated (see Table 3.6). Following September 2009, there is once again no change in false warnings observed. Following July 2011, there is an increase in the incidence of false warnings (***Post*** coefficient is 0.464). The coefficient on ***Post*S&PMS*** is negative and not significant, implying that countries in the bottom quartile of S&P market share do not show different outcomes from those in the top three quartiles (i.e. countries with lesser reputational concerns, greater competition). This evidence supports the notion that increased *rating conservatism* induced by regulation is driving the increased incidence of false warnings, rather than CRAs protecting their reputation. In other words, CRAs are downgrading FI ratings to avoid potentially exposing themselves to increased regulatory interventions. This is not dependent on reputational concerns because regulatory penalties are applied to CRAs irrespective of their reputation. This result again contrasts with evidence from US corporate ratings, whereby the DFA's impact on false warnings is significantly stronger for industries where CRAs had stronger reputation concerns.

Estimating Eq. (3.5) for May 2013, using ***Post1***, ***Post2*** and ***S&PMS***, the coefficients of the interaction terms are both insignificant, i.e. there are no different effects for countries where CRAs have weaker or stronger reputational concerns. This reinforces the hypothesis that *rating conservatism* drives the rating changes rather than CRAs protecting their reputation. The May 2013 regulatory update exacerbates the effect, as an increase in the number of unwarranted downgrades (i.e. false warnings) is observed and there is no difference between countries with different reputational concerns.

3.5.3 INFORMATIONAL CONTENT OF RATINGS

This Section compares stock market reactions to rating announcements before and after the establishment of ESMA in July 2011.[104] To preview the findings, there is a decrease in the informational content of rating downgrades and an increase for rating upgrades, which are both consistent with increased *rating conservatism*.

The event study results,[105] reported in Table 3.7, show that, prior to July 2011, rating downgrades resulted in a significant stock price reduction (-0.597%***). After July 2011, there

[104] The impact of the September 2009 regulatory update upon the stock market reaction to rating downgrades is also examined. The results from an event study and OLS model (see Table 3.7 and Table 3.8) are consistent with those of July 2011, i.e. a decrease in rating downgrade informational content and an increase in rating upgrade informational content. Consistent with *rating conservatism* hypothesis.

[105] The results for only notch rating announcements (excluding outlook and watch) are consistent, see Table A. 3.18).

is no significant response to downgrades. The t-test confirms a significant decrease (-0.624%**) in the reaction to downgrades in the whole sample in the post-regulatory period, indicating that negative credit signals are less informative in the post-regulatory period. The results are consistent when the sample is restricted to rating announcements by only Moody's and Fitch (see Table 3.7).[106] The OLS model (Eq. (3.7)) produces equivalent inferences. It shows that, prior to the 2011 regulatory change, rating downgrades elicit a significant stock price reduction of 0.483% (see Table 3.8). However, after the regulatory change, rating downgrades no longer do so (insignificant ***Post * Rating downgrade***).

One of the intended aims of the regulation is to reduce the mechanistic market reaction to rating downgrades and it could therefore be argued that this has been successful. However, this change may be also due in part to an increase in *rating conservatism* induced by the new regulation's discouragement of over-optimistic ratings. Following the regulation, there is an increase in unwarranted rating downgrades (false warnings, see Section 3.5.2). It follows logically that unwarranted downgrades hold less information for the market.

The impact of the regulatory change in July 2011 on stock market reactions to positive signals is also examined. Table 3.8 shows that abnormal stock returns for positive rating news are insignificant before the regulatory change and remain insignificant after the regulation. This is consistent with prior literature (e.g. Correa et al., 2014). However, the results from examining each CRA separately show that, following the regulation, rating upgrades by both S&P and Fitch elicit positive and significant abnormal returns (0.419% and 0.868% respectively, see Table A. 3.16).

The results of the OLS model (Eq. (3.7)) for upgrades show that, prior to the 2011 regulatory change, no significant reaction to rating upgrades is observed. Following the establishment of ESMA, a 0.445% reaction in stock prices is observed in response to rating upgrades (see Table 3.8). There is therefore some evidence for a limited increase in the informational content of upgrades. This is consistent with increased *rating conservatism*, in the sense that CRAs will expend more effort to ensure that rating upgrades are warranted and will thereby typically become more informative.

Lastly, the impact of reputational concerns is also considered. The results (see Table A. 3.17) of Eq. (3.8) show no significant difference in stock market reaction to FI rating downgrades between countries with greater and lesser reputational concerns following the regulatory

[106] The results are consistent to considering clustering (see Table A. 3.15 and Section 3.5.4).

change of July 2011. This indicates that reputational effects are not driving the decrease in the informational content of rating downgrades. These results support the overall findings of the negligible relevance of the *reputation hypothesis* in the European FI rating context. In contrast, the US corporate rating market demonstrates strong evidence of reputational effects, with downgrades in industries with stronger reputational concerns exhibiting a stronger stock market reaction (Dimitrov et al., 2015).

The impact of the May 2013 regulatory update upon the stock market reaction to rating downgrades is also examined. The event study results show a clear reduction in the informational content of the rating downgrades in the whole sample following the regulatory update (1.146%*** decrease in the market reaction, see Panel C of Table 3.7). The results from the OLS model (Eq. (3.7)) corroborate those of the event study as once again a significant negative reaction to rating downgrades is observed (-0.483%, see Table 3.8) prior to July 2011. This then disappears and a positive reaction (which indicates a lack of information) is observed following the May 2013 update (see Table 3.8). For rating upgrades, the OLS model shows no significant reaction to rating upgrades prior to July 2011, a significantly stronger market reaction after July 2011 and then an insignificant reaction following the May 2013 update. These results are consistent with *rating conservatism* hypothesis.

3.5.4 ROBUSTNESS TESTS

The regulation that targeted CRAs has been rolled out incrementally. The DFA was enacted in the US in July 2010, prior to the EU's implementation of reforms in July 2011 and May 2013. To identify whether the DFA was in some way driving the changes in the EU, Eq. (3.2) to Eq. (3.5) are estimated with the inclusion of DFA dummy variable (Table 3.9), that takes the value of one after 21st July 2010 and zero otherwise. The results are robust to the inclusion of the DFA. Rating levels still exhibit a clear decrease following the EU regulation (-0.304***). False warnings show a clear increase in the post-regulatory period (0.383***). DFA's introduction appears to have an impact, but it is much smaller than the impact from the European regulation. It is clear that the EU regulation rather than US regulation is driving the results.

It is feasible that the regulation has induced S&P, Moody's and Fitch to amend their FI rating policies in different ways, thus Eq. (3.2) to Eq. (3.5) are estimated separately for each CRA (see Table 3.10 and Table 3.11).[107] The results of Eq. (3.2) (decreasing rating levels) are consistent for all three CRAs, although Moody's reveals a stronger result than S&P and Fitch. The results of Eq. (3.4) show a significant increase in false warnings for Moody's and Fitch, while S&P exhibits a weaker insignificant result. It is possible that since S&P has a lesser presence in the EU, S&P may issue less inflated FI ratings and thus did not issue as many unwarranted downgrades following the regulatory reforms. The results of Eq. (3.3) and Eq. (3.5) show that in the post-regulatory period, none of the CRAs' rating downgrades generate a significant stock market response, while S&P and Fitch rating upgrades induce a positive stock market reaction.

Bedendo et al. (2018) argue that CRAs react to criticism (reputational shocks) by increasing rating quality to preserve their reputation. This occurs when CRAs promptly react to criticism by increasing rating quality and unjustifiably downgrading ratings in order to preserve their reputation (Bar-Isaac and Shapiro, 2013; Bedendo et al., 2018). There are arguably three major reputational shocks during the sample (i) the 2006-2008 financial crisis (the collapse of Lehman Brothers in September 2008), (ii) the EU sovereign debt crisis (April 2010, the date that S&P downgraded Greece to junk status) and (iii) the S&P court case (February 2013). To control for the impact of reputational shocks during the sample period, Eq. (3.2) and (3.4) are estimated with an additional dummy $\boldsymbol{RepShock_{i,j,t}}$ that captures periods of reputational shock for CRAs and takes the value of one for a period of one year after the reputational shock and zero otherwise.

The results of Eq. (3.2) in Table 3.12 show a significant reduction in ratings in the year following a shock and there also remains a significant impact from the regulation (***Post*** coefficient is -0.303***, the magnitude of the rating reduction due to ***Post*** has barely decreased at all). Thus, while reputational shocks may contribute to decreased rating levels, they are not solely responsible. The results of Eq. (3.4) show a significant increase in false warnings following both the reputational shock and the regulation. This is attributable both to CRAs seeking to protect their reputation after any shock and to the role of regulation.

Dilly and Mählmann (2016) show that rating quality is counter cyclical and ratings quality should be higher in an economic downturn. It would be expected that during the sample period (economic downturn) that ratings quality should increase. This would then predict a reduction in false warnings and an increase in the informational content of ratings announcements. The

[107] There is, however, not enough observations to examine the informational content of rating announcements from each CRA separately.

results are, however, that there is an increase in false warnings and a reduction in the informational content of rating downgrades. It can therefore be concluded that the results cannot be driven by cyclical effects.

An additional piece of regulation to consider is the new EU bail-in laws (from January 2016 but variable timing across countries), which shift some of the responsibility for bank resolution from the government to shareholders and creditors and thus could potentially impact FI rating levels. A dummy variable is included on a country-by-country basis to take account of the period when the law is introduced in that country (ISDA 2016). The results (see Table 3.13) of Eq. (3.2) to Eq. (3.5) are consistent and robust to the inclusion of the bail-in dummy. The bail-in variable is not significant in any estimated model.

The European sovereign debt crisis featured a concentration of rating downgrades in peripheral Euro-zone countries, namely Greece, Ireland, Italy, Portugal and Spain. The sample is dominated by FIs in other countries. Nevertheless, as robustness tests, Eq. (3.2) to Eq. (3.5), Eq. (3.7) and Eq. (3.8) are estimated with a sub-sample excluding these countries. The results (see Table A. 3.19 and Table A. 3.20) are consistent and show a clear impact of the regulation.

There are 32 cases of mergers where the coverage ratio is evaluated, 12 did not have the information available. In the absence of the information the two extremes are substituted for the 12 companies without information: (i) when all have a positive coverage ratio and (ii) when all have a negative coverage ratio. The results for Eq. (3.4) are consistent using either case. In case (i), the ***Post*** coefficient is 0.383***, the odds that a CRA would issue a false warning after July 2011 are 1.47 times greater than before (see Table 3.6) and in case (ii), the ***Post*** coefficient is 0.361***, the odds that a CRA would issue a false warning after July 2011 are 1.43 times greater than before (see Table A. 3.14). As can be seen, there is no significant change in the results between the two cases.

When examining the information content of rating announcements using an event study, it is important to consider the clustering of rating announcements (Williams et al., 2015; Hill and Faff, 2010). An independent rating event is defined as one where no other rating event occurs for the FI within 21 trading days (-10, +11), otherwise the event is a clustered event. There are 1,654 separate rating events in the sample, of which 1,263 are independent events and 391 are clustered. The results (see Table A. 3.15) are consistent, although independent rating downgrades generate a much greater market reaction prior to July 2011, whereas clustered downgrades do not. Both reveal insignificant reactions after July 2011.

Lastly, as explained in Sections 3.5.1 and 3.5.2, the results of Eq. (3.2) to Eq. (3.5) are consistent when they are estimated using Probit or OLS model (see Table A. 3.10) and to alternative specifications of the S&P market share dummy (see Table A. 3.13).[108] As stated in Section 3.4.2, the results for Eq. (3.4) and Eq. (3.5) are robust to alternative definitions of false warnings (see Table A. 3.5).[109] As stated in Section 3.5.1, the results to Eq. (3.2) and Eq. (3.3) are robust to the use of the 18-notch rating scale (see Table A. 3.2), which excludes outlook and watch signals. As stated in Section 3.4.1, the results from Eq. (3.2) to Eq. (3.8) are robust to using to using country and year fixed effects separately (see Table A. 3.11), and to using no fixed effects (see Table A. 3.12)[110] (as done by Dimitrov et al., 2015).

[108] Using 10% and 40% as the cut off, instead of 25%.
[109] Using B+ as the cut off and a period of 24 months.
[110] The results are also consistent for the May 2013 regulatory update (results available on request).

3.6 CONCLUSIONS

This Chapter investigates whether the EU regulatory reforms of the rating industry in response to the global financial crisis have been successful. The Chapter is also unique in its focus on the quality of FIs' ratings following the regulatory reform. A sample of 758 financial institutions across 27 European countries rated by S&P, Moody's and Fitch during January 2006 to June 2016 is used. The Chapter examines the impact of EU regulation on rating levels, the incidence of false warnings and the responsiveness of stock markets to credit rating signals (rating informativeness). Three dates are considered: firstly, September 2009 when the initial wave of regulation was enacted (CRA I), secondly, July 2011, when the newly established ESMA assumed responsibility for supervising and certifying CRAs operating in the EU (CRA II) and thirdly, the May 2013 regulatory update which instigated a new civil liability regime (CRA III).

Three hypotheses on the impact of the regulatory change on credit ratings are tested, namely the *disciplining*, *conservatism* and *reputation* hypotheses. The *disciplining hypothesis* proposes that the regulation succeeds in the objective of increasing rating quality, on the grounds that increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring. The *rating conservatism* hypothesis states that CRAs are exposed to more severe scrutiny and penalties by over-rating (being less conservative), rather than by under-rating (being more conservative). As a result, increased regulatory stringency, fines and liability, increase the penalties for over ratings and cause a shift to more conservative rating behaviour. The *reputation hypothesis* implies that CRAs may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FIs' financial characteristics, in order to protect and rebuild their reputation. The effect strengthens with increased reputational concerns.

The Chapter reveals that the EU regulatory reforms act to promote more conservative rating behaviour, an effect previously unobserved in the rating industry, leading to a reduction in the levels of European FI ratings (as hoped for by regulators (EC, 2016), see Section 3.5.1). A reduction in rating levels is observed following all three regulatory reforms (CRA I, II and III) and the magnitude of the effect (***Post***) increases after each subsequent update indicating that the subsequent updates (CRA II and III) strengthen the existing effect of the regulation. While there is some evidence to support the presence of reputational effects following the shock of the 2008 financial crisis, these soon dissipate and by July 2011 the effect of the regulation does not vary with the strength of reputational concerns, indicating no evidence supporting the *reputation hypothesis*.

The decrease in FI rating levels occurs as CRAs err on the side of caution, given that overly generous ratings are much more likely to incur scrutiny and criticism. Since the decrease is not justified by the FIs underlying characteristics, but rather by changing CRA behaviour, it led to an increased incidence of unjustified downgrades (false rating warnings, see Section 3.5.2) and with it a corresponding decrease in the informational content of (and stock price reactions to) rating downgrades (see Section 3.5.3). The May 2013 regulatory update once again strengthens the existing impact of the regulation, by triggering a further increase in unjustified rating downgrades as CRAs face increased liability under the new civil liability regime (intensifies the conservative bias). There is no evidence of any change in false warnings following the initial publication of the regulation in September 2009, indicating the subsequent decrease in rating levels was warranted. The lack of an unjustified decrease at that time was due to the lack of effective enforcement of the regulation prior to the establishment of ESMA.[111]

The latter decrease in the informational content is consistent with increased *rating conservatism*, as unjustified downgrades are naturally of lower quality and less informative. But, the decrease in informational content may also be driven in part by a declining reliance on CRAs by market participants, which reduces the mechanistic reactions to rating signals in financial markets (a key aim of ESMA, see Section 2.3.2). There is evidence of increased stock price sensitivity to rating upgrades (mainly those by S&P and Fitch) following July 2011. This is consistent with the increased presence of *rating conservatism*, as CRAs spend more effort and resources to ensure that upgrades are justified in an environment of increased regulatory scrutiny and potential legal repercussions. While there is some evidence for the presence of reputational concerns in September 2009 following the 2008 financial crisis,[112] these dissipate in the post regulatory period and by July 2011 they are completely gone. These results are robust to the inclusion of the US Dodd-Frank Act, reputational shocks, the new EU bail-in laws and to alternative definitions of false warnings and of the rating scale (see Section 3.5.4).

[111] Hence, the regulation of September 2009 did not increase the liability or potential regulatory action against CRAs prior to the establishment of ESMA. The result shows no increase in *rating conservatism* at that time.
[112] This acted as a reputational shock, heightening reputational concerns for CRAs in the subsequent period (see Bedendo et al. (2018) and Section 3.5.4).

The results contrast with evidence from US corporate bond ratings where it appears that reputational effects have driven changes in CRA behaviour subsequent to the DFA (see Section 2.3.5). Becker and Milbourn (2011) and Dimitrov et al. (2015) propose that incumbent CRAs have greater reputational concerns (are less competitive) in markets with the presence of a third CRA with a smaller market share (markets with less competition). In contrast to the US, for EU FIs, the Chapter finds no evidence of variation in effect between countries with differing reputational concerns. The regulatory update of May 2013 strengthens the existing impact of the regulation on *rating conservatism* by further reducing rating levels and increasing unwarranted downgrades.

Although the EU and US CRA regulatory reforms have some similarities, there are substantial differences in the details and execution. ESMA has been much more active in enforcing the regulatory amendments than the US SEC, e.g. CRAs have been fined by ESMA three times for violations of the EU regulations, while there have been no fines levied by SEC. This Chapter considers the incremental effect of the EU regulation, alongside the earlier introduction of DFA to regulate CRAs in the US (see Section 3.5.4). The results are robust to the consideration of DFA and this Chapter finds that the EU regulation has a far more significant impact, as would be expected.

While the regulation has been successful in reducing rating inflation, the evidence indicates that this is a by-product of a behavioural shift towards increased *rating conservatism*, rather than a result of increased rating quality. This has come at the cost of an increased incidence of false warnings and reduced rating downgrade informativeness, but there is evidence of reducing mechanistic market reactions to rating downgrades. This is not the first time CRA regulation has produced some unintended consequences (Behr et al., 2018). Credit ratings are an important source of information for market participants and therefore regulators should reflect on the need to alleviate both overly optimistic and conservative biases in the ratings industry and to consider the costs of reducing the informational content of rating downgrades. Regulators should also more explicitly consider the structured debt-rating sector separately from the FI rating segment, given that the Chapter finds evidence that increased competition among CRAs leads to more inflated FI ratings.

TABLES

Table 3.1: Distribution of FIs in the sample

	Including Volksbanks				Excluding Volksbanks			
Country	Total	S&P	Moody's	Fitch	Total	S&P	Moody's	Fitch
Austria	89	11	23	71	26	9	14	15
Belgium	11	9	7	9	11	9	7	9
Bulgaria	19	5	9	11	18	5	8	10
Cyprus	5	2	4	5	5	2	4	5
Czech Republic	6	4	6	3	6	4	6	3
Germany	1707	1336	59	1678	115	76	48	92
Denmark	14	6	13	5	14	6	13	5
Estonia	3	0	3	1	3	0	3	1
Spain	86	27	56	63	86	27	56	63
Finland	9	7	6	5	9	7	6	5
France	169	97	93	91	87	51	37	51
UK	88	36	67	64	88	36	67	64
Greece	11	7	10	8	11	7	10	8
Hungary	10	3	9	5	10	3	9	5
Ireland	24	16	19	14	23	15	19	13
Italy	106	65	64	57	103	63	61	57
Lithuania	6	2	3	5	6	2	3	5
Luxemburg	26	15	16	9	24	13	15	8
Latvia	10	1	10	3	10	1	10	3
Malta	2	0	1	2	2	0	1	2
Netherlands	22	15	19	16	22	15	19	16
Poland	19	3	14	15	19	3	14	15
Portugal	18	9	11	15	18	9	11	15
Romania	12	2	4	9	11	2	3	9
Sweden	13	10	11	5	13	10	11	5
Slovenia	9	2	5	7	9	2	5	7
Slovakia	9	1	8	3	9	1	8	3
Total	2503	1691	550	2179	758	378	468	494

The table reports the number of FIs in each country rated by each CRA present in the sample. It also details the number of Volksbanks (small regional banks), which are removed from the data sample.

Table 3.2: Control variables description and summary statistics

Section	Variable	Explanation	Measure	Anticipated relation to CCR	Observations	Mean	Std.	Min	Max
Main factors	*Post*	Post regulatory change, dummy variable of one for observations after the regulatory change, zero otherwise.	Regulatory change	-					
	S&PMS	S&P market share	Reputational concerns	+/-					
Rating variables	*Moody*	Moody's rating dummy variable	Rating by Moody	+/-					
	Fitch	Fitch rating dummy variable	Rating by Fitch	+/-					
Bank specific variables (*BANK*)	*LLPNIR*	Ratio of loan-loss provisions to net interest revenues	Asset Quality	+	105,756	23.54	27.74	-75.76	160.20
	CIR	Ratio of cost to income	Efficiency	-	105,756	59.44	15.34	19.21	113.35
	ROAA	Return on average assets	Profitability	+	105,756	0.51	0.70	-3.73	3.82
	NIIGR	Non-interest income over gross revenue	Revenues	+	105,756	34.26	18.84	-14.99	93.11
	ETA	Ratio of equity total assets	Leverage	+	105,756	7.01	3.91	1.04	35.16
	LAtoCSTF	Ratio of liquid assets to customer and short term funding	Liquidity	+	105,756	32.64	27.66	1.53	148.44
	Ln(TA)	The natural logarithms of total assets (€)	Size	+	105,756	17.08	2.25	10.75	22.06
Dummy variables	*RF*	Dummy variable for each country	Geographic variation						
	YF	Dummy variable for each year	Variation over time						

Details the variables used in the regression model of rating levels. S&P is used as base category for the CRA dummies. The sample consists of European rated FIs with rating announcements during the period January 2006 to June 2016 in the 27 EU countries included.

Table 3.3: Rating announcement descriptive statistics

	CCR (outlook and watch)	
	Downgrades	Upgrades
Sample	Observations	Observations
S&P	398	142
Moody's	379	191
Fitch	331	97

	Number of events	
CCR point change	Downgrades	Upgrades
1	275	166
2	207	80
3	345	116
4	50	34
5	39	4
6	129	22
7	6	1
8	5	0
9	34	7
10 or more	18	0

The occurrences of rating upgrades and downgrades throughout the sample. This table separates the rating events by CRA, by type and by the magnitude of the change.

Table 3.4: Impact of S&P market share

Variable	Moody's and Fitch		Moody's		Fitch	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
S&PMS	-1.804***	-5.62	-1.418***	-7.98	-1.126**	-2.09
Moody's	-0.519***	-5.27				
ROAA	-0.030	-0.25	0.030	0.21	0.015	0.14
CIR	-0.017***	-3.47	-0.019***	-3.80	-0.016***	-3.01
LLPNIR	-0.011***	-3.06	-0.012***	-3.61	-0.008**	-2.14
Ln(TA)	0.302**	2.02	0.524***	7.36	0.181	1.20
NIIGR	0.006**	2.00	0.003	0.80	0.007**	2.11
ETA	0.006	0.43	0.038**	1.99	-0.026	-1.38
LAtoCSTF	0.000	0.02	0.004	0.66	-0.003	-0.74
Country * Year FE	Yes		Yes		Yes	
# Observations	75,631		35,478		40,153	
Pseudo R^2	10.69%		12.80%		12.70%	

The table reports the results of the ordered logit model, Eq. (3.1). The dependent variable is the FI credit rating (based on the 52 point CCR scale). The key independent variable is ***S&PMS$_{t-1}$****, S&P market share (lagged by 1 year), defined as a dummy variable with a value 1 for FIs in countries within the lower quartile of S&P market share and zero within the upper three quartiles of S&P market share. The sample includes 758 rated European FIs during the period January 2006 to June 2016 in the 27 EU. See Table 3.2 for the definitions of control variables. Standard errors are clustered by FI and a full set of* ***country*year dummies*** *are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3.5: Rating levels

	Eq. (3.2)						Eq. (3.3)					
	September 2009		July 2011		May 2013		September 2009		July 2011		May 2013	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.179***	-9.67	-0.304***	-8.17	-0.304***	-8.17	-0.188***	-8.47	-0.345***	-7.77	-0.345***	-7.77
Post1					-0.413***	-9.38					-0.427***	-8.44
Post2											-1.303	-1.64
S&PMS							-1.420	-1.78	-1.399*	-1.76		
Post × S&PMS							-0.195**	-2.34	-0.061	-0.47		
Post1 × S&P market share											-0.061	-0.47
Post2 × S&P market share											-0.155	-0.84
Moody's	-0.036	-0.40	-0.037	-0.41	-0.037	-0.41	-0.519***	-6.25	-0.520***	-6.25	-0.520***	-6.25
Fitch	0.416***	5.07	0.416***	5.07	0.416***	5.07						
ROAA	-0.086	-0.88	-0.087	-0.88	-0.087	-0.88	-0.029	-0.29	-0.030	-0.30	-0.030	-0.30
CIR	-0.015***	-3.55	-0.015***	-3.55	-0.015***	-3.55	-0.017***	-3.89	-0.017***	-3.89	-0.017***	-3.89
LLPNIR	-0.010***	-4.68	-0.010***	-4.67	-0.010***	-4.68	-0.011***	-4.47	-0.011***	-4.46	-0.011***	-4.46
Ln(TA)	0.220***	5.51	0.220***	5.52	0.220***	5.52	0.302***	7.56	0.302***	7.56	0.302***	7.56
NIIGR	0.008**	2.37	0.008**	2.37	0.008**	2.37	0.006*	1.69	0.006*	1.69	0.006*	1.69
ETA	-0.002	-0.07	-0.001	-0.07	-0.002	-0.07	0.006	0.28	0.006	0.29	0.006	0.29
LAtoCSTF	-0.000	-0.02	-0.000	-0.02	-0.000	-0.02	0.000	0.03	0.000	0.03	0.000	0.03
Country * Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
# Observations	105,756		105,756		105,756		75,631		75,631		75,631	
Pseudo R^2	10.20%		10.21%		10.21%		10.69%		10.70%		10.70%	

The table presents the results of the ordered logit regressions for the sample of European FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch in Eq. (3.2), and by Moody's and Fitch in Eq. (3.3). Three different regulatory start dates are included. First, September 2009 when CRA I was enacted, second July 2011 when ESMA was established and lastly, May 2013 when the regulatory update was released. The dependent variable is $\boldsymbol{CR_{i,j,k,t}}$*: the credit rating level of FI i in country j by CRA k at time t based on a 52-point CCR rating scale.* ***Post*** *is a dummy variable that takes the value of 1 after September 2009/July 2011 and zero otherwise. When both regulatory changes are considered,* ***Post1*** *takes the value of one between July 2011 and May 2013, zero otherwise.* ***Post2*** *takes the value of one after May 2013 and zero otherwise.* ***S&PMS*** *is a dummy variable that takes the value of 1 in countries in the bottom quartile of S&P market share and zero in the top three quartiles.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions, see Table 3.2. Standard errors are clustered by FI and a full set of* ***year*country dummies*** *are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3.6: False warnings

	Eq. (3.4)						Eq. (3.5)					
	September 2009		July 2011		May 2013		September 2009		July 2011		May 2013	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.008	0.17	0.383***	3.57			0.015	0.46	0.464***	4.02		
Post1					0.383***	3.57					0.464***	4.02
Post2					0.694***	5.52					0.704***	5.11
S&PMS							0.706	0.54	0.542	0.40	0.542	0.40
Post × S&PMS							-0.020	-0.50	-0.032	-0.11		
Post1 × S&PMS											-0.032	-0.11
Post2 × S&PMS											0.052	0.15
Moody's	0.152	0.76	0.153	0.77	0.153	0.77	0.681***	2.95	0.682***	2.95	0.683***	2.95
Fitch	-0.562***	-2.58	-0.562***	-2.58	-0.562***	-2.58						
ROAA	0.061	0.44	0.061	0.43	0.061	0.43	0.048	0.30	0.048	0.29	0.048	0.29
CIR	0.001	0.18	0.001	0.18	0.001	0.18	0.006	0.81	0.006	0.82	0.006	0.81
LLPNIR	0.012***	3.32	0.012***	3.32	0.012***	3.32	0.012***	2.97	0.012***	2.96	0.012***	2.97
Ln(TA)	-0.435***	-6.26	-0.436***	-6.26	-0.436***	-6.26	-0.465***	-6.11	-0.466***	-6.11	-0.466***	-6.11
NIIGR	-0.002	-0.34	-0.002	-0.34	-0.002	-0.34	0.002	0.29	0.002	0.29	0.002	0.29
ETA	-0.025	-0.86	-0.025	-0.86	-0.025	-0.86	-0.038	-1.16	-0.038	-1.16	-0.038	-1.16
LAtoCSTF	0.011**	2.37	0.011**	2.36	0.011**	2.36	0.010**	2.03	0.010**	2.02	0.010**	2.02
Country * Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
# Observations	91,353		91,353		91,353		59,263		59,263		59,263	
Pseudo R^2	36.58%		36.61%		36.64%		34.09%		34.14%		34.16%	

The table presents the results of logit regressions for the sample of rated European FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch in Eq. (3.4), and by Moody's and Fitch in Eq. (3.5). Three different regulatory start dates are included. First, September 2009 when CRA I was enacted, second July 2011 when ESMA was established and lastly, May 2013 when the regulatory update was released. The dependent variable $\boldsymbol{FW_{i,j,k,t}}$*, a dummy representing false warnings, takes the value of 1 if an FI with a rating of BB+ or below does not default after one year and zero otherwise.* ***Post*** *is a dummy variable that takes the value of 1 after September 2009/July 2011 and zero otherwise. When both regulatory changes are considered,* ***Post1*** *takes the value of one between July 2011 and May 2013, zero otherwise.* ***Post2*** *takes the value of one after May 2013 and zero otherwise.* ***S&PMS*** *is a dummy variable that takes the value of 1 in countries in the bottom quartile of S&P market share and zero in the top three quartiles.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions see Table 3.2. Standard errors are clustered by FI and a full set of* ***year*country dummies*** *are included. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table 3.7: Informational content – Event study

Panel A: September 2009

	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic
Credit rating downgrades	Whole sample	#Obs	272	836		
		Mean return (%)	-0.938***	-0.025	-0.913***	-3.03
	Moody's and Fitch	#Obs	153	557		
		Mean return (%)	-0.885**	-0.036	-0.848**	-2.26
Credit rating upgrades	Whole sample	#Obs	109	321		
		Mean return (%)	-0.260	0.112	-0.372	-1.28
	Moody's and Fitch	#Obs	72	216		
		Mean return (%)	0.079	-0.032	0.111	0.31

Panel B: July 2011

	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic
Credit rating downgrades	Whole sample	#Obs	490	618		
		Mean return (%)	-0.597***	0.027	-0.624**	-2.39
	Moody's and Fitch	#Obs	304	406		
		Mean return (%)	-0.595**	0.062	-0.657**	-2.10
Credit rating upgrades	Whole sample	#Obs	144	286		
		Mean return (%)	-0.186	0.120	-0.307	-1.15
	Moody's and Fitch	#Obs	93	195		
		Mean return (%)	0.027	-0.019	0.046	0.14

Panel C: May 2013

	Sample	Variable	Post = 0	Post = 1	Difference	T-statistic
Credit rating downgrades	Whole sample	#Obs	904	204		
		Mean return (%)	-0.460***	0.686**	-1.146***	-3.43
	Moody's and Fitch	#Obs	575	135		
		Mean return (%)	-0.431***	0.684	-1.115***	-2.84
Credit rating upgrades	Whole sample	#Obs	180	250		
		Mean return (%)	0.037	0.004	0.033	0.13
	Moody's and Fitch	#Obs	121	267		
		Mean return (%)	0.272	-0.204	0.476	1.55

The table presents the results of the event study for the stock market reaction (abnormal return) to credit rating signals (including outlook and watch) for the sample of 758 rated European FIs during the period January 2006 to June 2016 in the 27 EU countries. ***Post*** *is defined as the September 2009/July 2011/May 2013 in Panel A, B and C respectively. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table 3.8: Informational content – OLS model

	Rating Downgrades						Rating Upgrades					
	September 2009		July 2011		July 2011 and May 2013		September 2009		July 2011		July 2011 and May 2013	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.334***	-6.05	-0.051*	-1.83			-0.332***	-6.04	-0.051*	-1.81		
Post1					-0.050*	-1.81					-0.051*	-1.82
Post2					-0.068	-1.60					-0.069	-1.59
Rating Downgrade	-0.667	-1.45	-0.483*	-1.72	-0.483*	-1.72						
Rating Upgrade							-0.202	-1.17	-0.134	-1.12	-0.134	-1.12
Post × Rating Downgrade	0.455	1.01	0.299	0.98								
Post1 × Rating Downgrade					0.190	0.59						
Post2 × Rating Downgrade					0.589*	1.96						
Post × Rating Upgrade							0.484*	1.85	0.445**	2.20		
Post1 × Rating Upgrade											1.625**	2.03
Post2 × Rating Upgrade											0.278	1.42
Moody's	-0.017	-1.49	-0.015	-1.36	-0.015	-1.32	-0.014	-1.21	-0.013	-1.19	-0.013	-1.17
Fitch	-0.006	-0.49	-0.006	-0.50	-0.006	-0.51	-0.003	-0.24	-0.004	-0.29	-0.005	-0.37
ROAA	0.076	0.97	0.073	0.93	0.073	0.93	0.075	0.96	0.073	0.94	0.073	0.93
CIR	0.007*	1.94	0.007*	1.93	0.007*	1.93	0.007*	1.93	0.007*	1.93	0.007*	1.93
LLPNIR	0.003	0.92	0.003	0.93	0.003	0.93	0.003	0.91	0.003	0.92	0.003	0.92
Ln(TA)	0.014	0.95	0.014	0.94	0.014	0.96	0.014	0.96	0.014	0.95	0.014	0.96
NIIGR	0.003	1.21	0.003	1.21	0.003	1.21	0.003	1.23	0.003	1.22	0.003	1.22
ETA	-0.008	-0.75	-0.008	-0.79	-0.008	-0.78	-0.008	-0.75	-0.008	-0.78	-0.008	-0.78
LAtoCSTF	-0.004**	-2.45	-0.004**	-2.47	-0.004**	-2.48	-0.004**	-2.46	-0.004**	-2.48	-0.004**	-2.49
Country * Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
# Observations	443,641		443,641		443,641		443,641		443,641		443,641	
R^2	0.001%		0.001%		0.001%		0.001%		0.001%		0.001%	

The table presents the results of Eq. (3.7). The dependent variable is AR, the abnormal stock return and is calculated as shown in Eq. (3.6). ***Rating upgrade*** *and* ***Rating downgrade*** *are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise. Only cases with the full window [-230, -30] are considered.* ***Post*** *is a dummy variable that takes the value of 1 after September 2009/July 2011 and zero otherwise.* ***Post1*** *takes the value of one between July 2011 and May 2013, zero otherwise and* ***Post2*** *takes the value of one after May 2013 and zero otherwise.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions see Table 3.2. The Sample includes 758 rated European FIs during the period January 2006 to June 2016 in the 27 EU countries. Post, Rating downgrade and Rating upgrade, Post* Rating downgrade, Post* Rating upgrade are multiplied by 100 to give the impact on the percentage abnormal return. Standard errors are clustered by company and a full set of* ***country*year dummies*** *are included. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table 3.9: Incremental effect of the regulation

Panel A - Rating levels

Variable	Eq. (3.2)	Eq. (3.2)	Eq. (3.3)	Eq. (3.3)
Post Dodd Frank	-0.095***	-0.095***	-0.115***	-0.115***
Post	-0.304***		-0.345***	
Post1		-0.179***		-0.345***
Post2		-0.288***		-0.427***
S&PMS			-1.279	-1.183
Post Dodd Frank * S&PMS			-0.005	-0.005
Post * S&PMS			-0.061	
Post1 * S&PMS				-0.061
Post2 * S&PMS				-0.155
Controls	Yes	Yes	Yes	Yes
Country * Year FE	Yes	Yes	Yes	Yes
# Observations	105,756	105,756	75,631	75,631
Pseudo R^2	10.21%	10.20%	10.70%	10.71%

Panel B - False warnings

Variable	Eq. (3.4)	Eq. (3.4)	Eq. (3.5)	Eq. (3.5)
Post Dodd Frank	0.224**	0.224**	0.263**	0.263**
Post	0.383***		0.464***	
Post1		0.383***		0.464***
Post2		0.694***		0.704***
S&PMS			0.722	0.722
Post Dodd Frank * S&PMS			-0.444**	-0.444**
Post * S&PMS			-0.032	
Post1 * S&PMS				-0.032
Post2 * S&PMS				0.052
Controls	Yes	Yes	Yes	Yes
Country * Year FE	Yes	Yes	Yes	Yes
# Observations	91,353	91,242	59,263	59,263
Pseudo R^2	36.62%	36.65%	34.15%	34.17%

*The table presents the results of the ordered logit regressions for the sample of European FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch in Eq. (3.2) and (3.3), and by Moody's and Fitch in Eq. (3.4) and (3.5). Three different regulatory start dates are included. First, July 2011 when ESMA was established, second May 2013 when the regulatory update was released and third, July 2010 when Dodd-Frank Act was implemented in the US. The dependent variable in Panel A is $\boldsymbol{CR_{i,j,k,t}}$: the credit rating level of FI i in country j by CRA k at time t based on a 52-point CCR rating scale, and in Panel B is $\boldsymbol{FW_{i,j,k,t}}$, a dummy representing false warnings, takes the value of 1 if an FI with a rating of BB+ or below does not default after one year and zero otherwise. **Post** is a dummy variable that takes the value of 1 after July 2011 (establishment of ESMA) and zero otherwise. When both regulatory changes are considered, **Post1** takes the value of one between July 2011 and May 2013, zero otherwise. **Post2** takes the value of one after May 2013 and zero otherwise. **Post Dodd-Frank** takes the value of 1 after July 2010 and zero otherwise. **S&PMS** is a dummy variable that takes the value of 1 in countries in the bottom quartile of S&P market share and zero in the top three quartiles. **Moody's** and **Fitch** are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions, see Table 3.2. Standard errors are clustered by FI and a full set of **country*year dummies** are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3.10: Rating levels - S&P, Moody's and Fitch separately

Panel A: Eq. (3.2)

	S&P		Moody's		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.178***	-4.46	-0.476***	-8.75	-0.207***	-5.34
ROAA	-0.126	-0.77	0.030	0.23	0.054	0.53
CIR	-0.009*	-1.77	-0.019***	-3.54	-0.012***	-2.65
LLPNIR	-0.007**	-2.51	-0.012***	-3.61	-0.006***	-2.75
Ln(TA)	0.025	0.49	0.525***	9.51	0.133***	3.50
NIIGR	0.012***	2.70	0.003	0.61	0.006	1.51
ETA	-0.019	-0.68	0.039	1.44	-0.029	-1.33
LAtoCSTF	0.000	0.13	0.004	1.06	-0.001	-0.54
Country * Year FE	Yes		Yes		Yes	
# Observations	30,125		35,478		40,153	
Pseudo R^2	11.73%		12.83%		11.67%	

Panel B - Eq. (3.3)

	Moody's		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.468***	-8.39	-0.205***	-4.88
S&PMS	-0.863	-0.60	-0.492	-0.89
Post × S&PMS	-0.088	-0.44	-0.140	-1.32
ROAA	0.030	0.23	0.047	0.46
CIR	-0.019***	-3.54	-0.012***	-2.78
LLPNIR	-0.012***	-3.61	-0.006***	-2.86
Ln(TA)	0.525***	9.51	0.138***	3.60
NIIGR	0.003	0.61	0.006	1.56
ETA	0.039	1.44	-0.029	-1.32
LAtoCSTF	0.004	1.06	-0.002	-0.61
Country * Year FE	Yes		Yes	
# Observations	35,478		40,153	
Pseudo R^2	12.83%		11.78%	

The Table presents the results of the ordered logit regressions for the sample of European FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch separately. The dependent variable is $\boldsymbol{CR_{i,j,k,t}}$*: the credit rating level of FI i in country j by CRA k at time t based on a 52-point CCR rating scale.* ***Post*** *is a dummy variable that takes the value of 1 July 2011 and zero otherwise.* ***S&PMS*** *is a dummy variable that takes the value of 1 in countries in the bottom quartile of S&P market share and zero in the top three quartiles. For control variables' definitions, see Table 3.2. Standard errors are clustered by FI and a full set of* ***year*country dummies*** *are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3.11: False warnings - S&P, Moody's and Fitch separately

Panel A: Eq. (3.4)

	S&P		Moody's		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.166	0.62	0.814***	4.49	0.197**	2.01
ROAA	0.014	0.05	0.009	0.05	0.177	0.74
CIR	-0.016	-1.07	0.008	0.85	0.012	1.06
LLPNIR	0.016***	2.62	0.013***	2.82	0.015**	2.49
Ln(TA)	-0.393***	-3.62	-0.594***	-4.67	-0.521***	-4.14
NIIGR	-0.009	-0.79	0.000	-0.04	0.003	0.36
ETA	0.018	0.40	-0.139***	-3.17	0.042	0.96
LAtoCSTF	0.019*	1.71	0.003	0.61	0.012	1.60
Country * Year FE	Yes		Yes		Yes	
# Observations	18,439		24,214		25,188	
Pseudo R^2	38.12%		35.25%		30.81%	

Panel B: Eq. (3.5)

	Moody's		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.833***	4.46	0.104	1.07
S&PMS	-0.297	-0.19	-1.128	-0.92
Post × S&PMS	-0.307	-0.41	0.423	1.37
ROAA	0.009	0.05	0.177	0.74
CIR	0.008	0.85	0.012	1.06
LLPNIR	0.013***	2.82	0.015**	2.49
Ln(TA)	-0.594***	-4.67	-0.522***	-4.14
NIIGR	0.000	-0.04	0.003	0.36
ETA	-0.139***	-3.17	0.042	0.96
LA to CSTF	0.003	0.61	0.012	1.60
Country * Year FE	Yes		Yes	
# Observations	24,214		25,188	
Pseudo R^2	35.25%		30.82%	

Logit regression for the EU sample which includes ratings by S&P, Moody's and Fitch (S&P and Moody's for Eq. (3.5)). Post starts after the 1st July 2011 and the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and* ***country*year*** *interactions are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 3.12: Reputational shocks

	Eq. (3.1)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.303***	-8.07	0.405***	4.02
Reputational Shock	0.000	0.05	0.037	0.75
Post × Reputational Shock	-0.059***	-3.93	0.167**	2.55
Moody's	-0.037	-0.41	0.153	0.77
Fitch	0.416***	5.07	-0.562***	-2.58
ROAA	-0.087	-0.88	0.061	0.43
CIR	-0.015***	-3.55	0.001	0.18
LLPNIR	-0.010***	-4.67	0.012***	3.32
Ln(TA)	0.220***	5.52	-0.436***	-6.26
NIIGR	0.008**	2.37	-0.002	-0.34
ETA	-0.001	-0.07	-0.025	-0.86
LAtoCSTF	0.000	-0.02	0.011**	2.36
Country * Year FE	Yes		Yes	
# Observations	105,756		91,353	
Pseudo R^2	10.21%		36.63%	

Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.3) and Eq. (3.4) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.2) and Eq. (3.4)). Post start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale). In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. The post has been interacted with a reputational shock dummy that takes the value of one in the year following a reputational shock and zero otherwise. Reputational shocks take place on the 1st September 2008, 27th April 2010 and the 4th February 2013. Standard errors are clustered by company and ***country*year*** *interactions are included. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table 3.13: The bail-in regime

Panel A: Rating levels

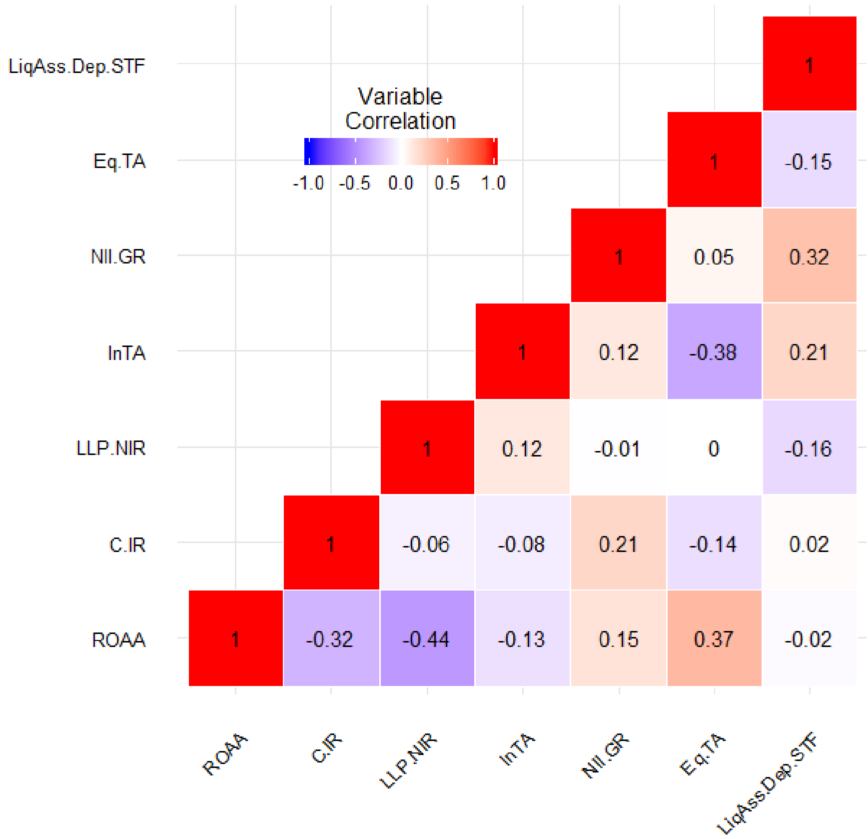
	Eq. (3.2)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.304***	-8.17	-0.345***	-7.77
S&PMS			-1.399*	-1.76
Post × S&PMS			-0.061	-0.47
Bail In	0.021	0.51	0.039	0.79
Moody's	-0.037	-0.41	-0.520	-6.25
Fitch	0.416***	5.07		
ROAA	-0.087	-0.88	-0.030	-0.30
CIR	-0.015***	-3.55	-0.017***	-3.89
LLPNIR	-0.010***	-4.67	-0.011***	-4.46
Ln(TA)	0.220***	5.52	0.302***	7.56
NIIGR	0.008**	2.37	0.006*	1.69
ETA	-0.001	-0.07	0.006	0.29
LAtoCSTF	0.000	-0.02	0.000	0.03
Country * Year FE	Yes		Yes	
# Observations	105,756		75,631	
Pseudo R^2	10.21%		10.70%	

Panel B: False warnings

	Eq. (3.4)		Eq. (3.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.383***	3.57	0.464***	4.02
S&PMS			0.542	0.40
Post × S&PMS			-0.032	-0.11
Bail In	-0.036	-0.38	0.051	0.44
Moody's	0.153	0.77	0.682***	2.95
Fitch	-0.562***	-2.58		
ROAA	0.061	0.43	0.048	0.29
CIR	0.001	0.18	0.006	0.82
LLPNIR	0.012***	3.32	0.012***	2.96
Ln(TA)	-0.436***	-6.26	-0.466***	-6.11
NIIGR	-0.002	-0.34	0.002	0.29
ETA	-0.025	-0.86	-0.038	-1.16
LAtoCSTF	0.011**	2.36	0.010**	2.02
Country * Year FE	Yes		Yes	
# Observations	91,353		59,263	
Pseudo R^2	36.61%		34.14%	

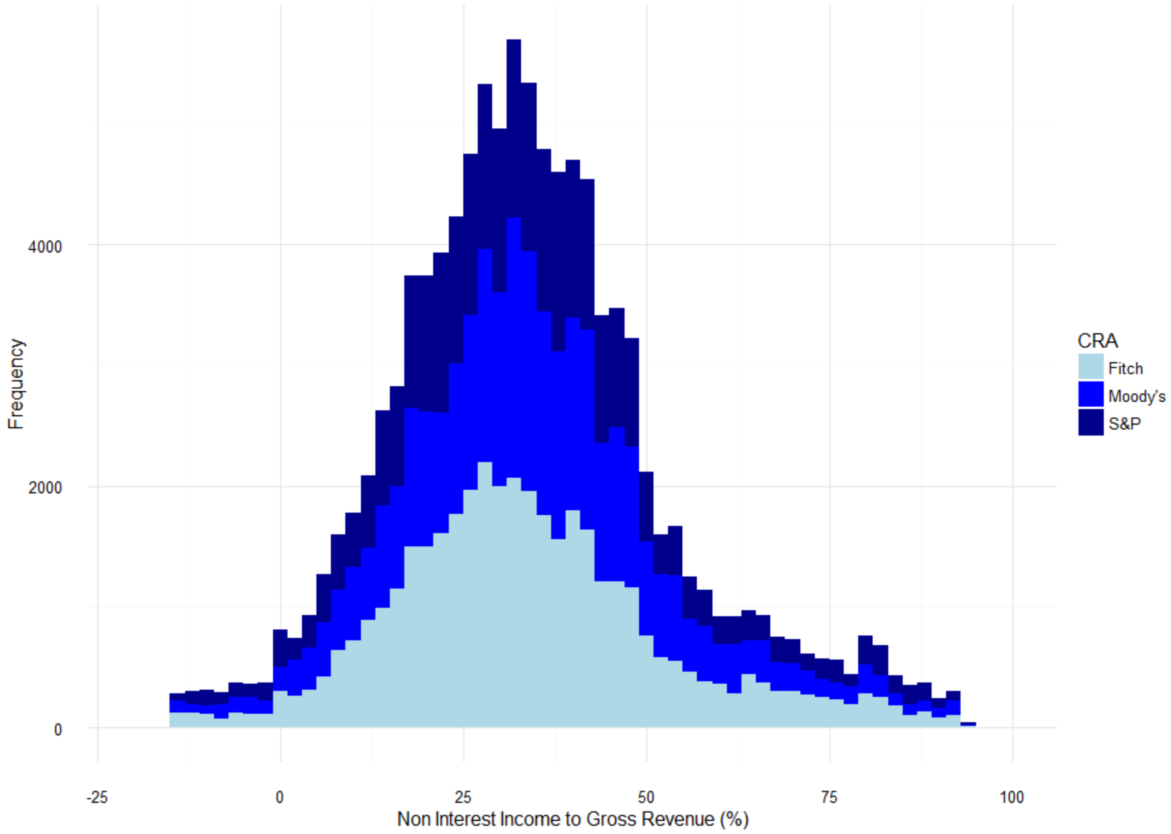
*Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). **Post** start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale). In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. **S&PMS** is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. A bail in dummy that takes the value of 1 following the implementation of the bail-in regulation in the country and zero before. Different bail in dates are used for each country as they implemented the bail in regulation at different times. Standard errors are clustered by company and **country*year** interactions are included. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Figure 3.1: Control variable correlation matrix



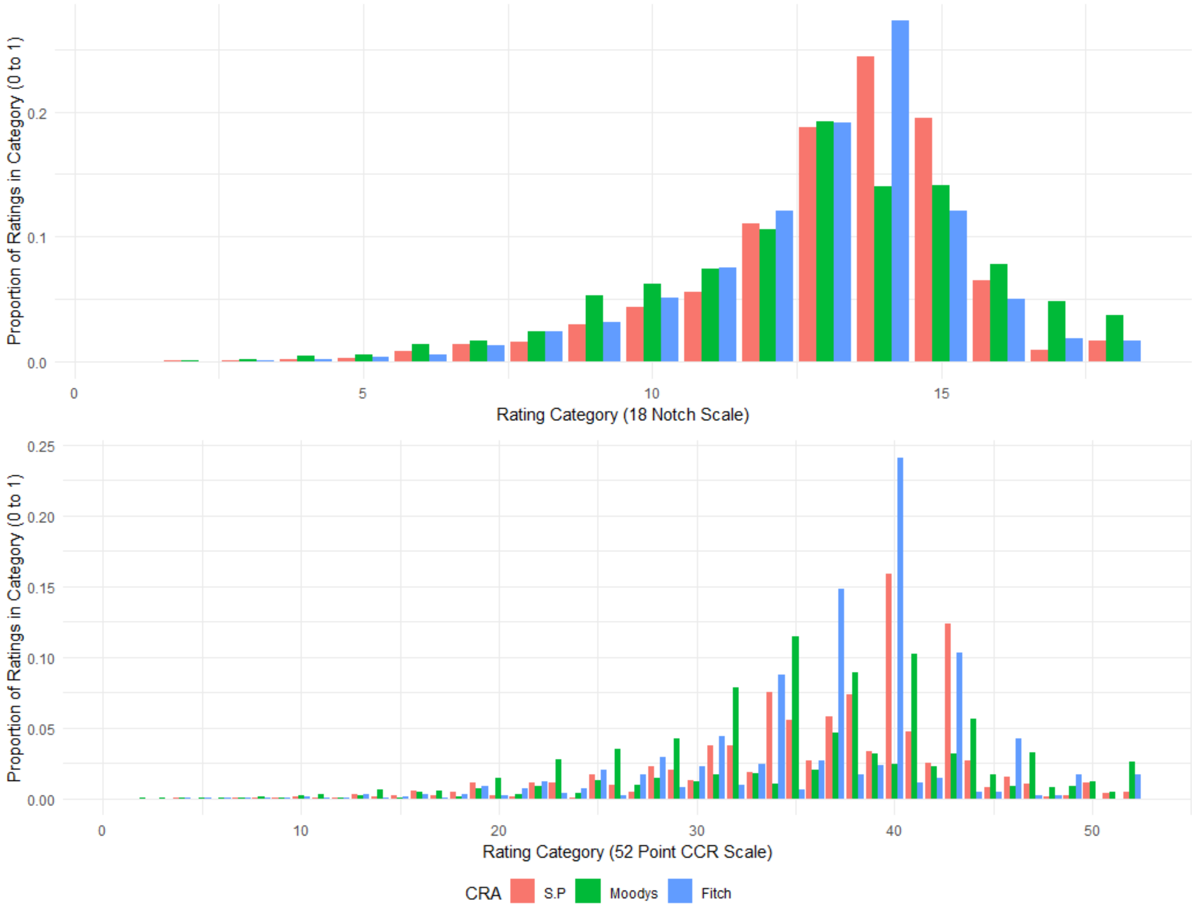
Correlation matrix for the banking variables listed in Table 3.2.

Figure 3.2: NII-GR distribution



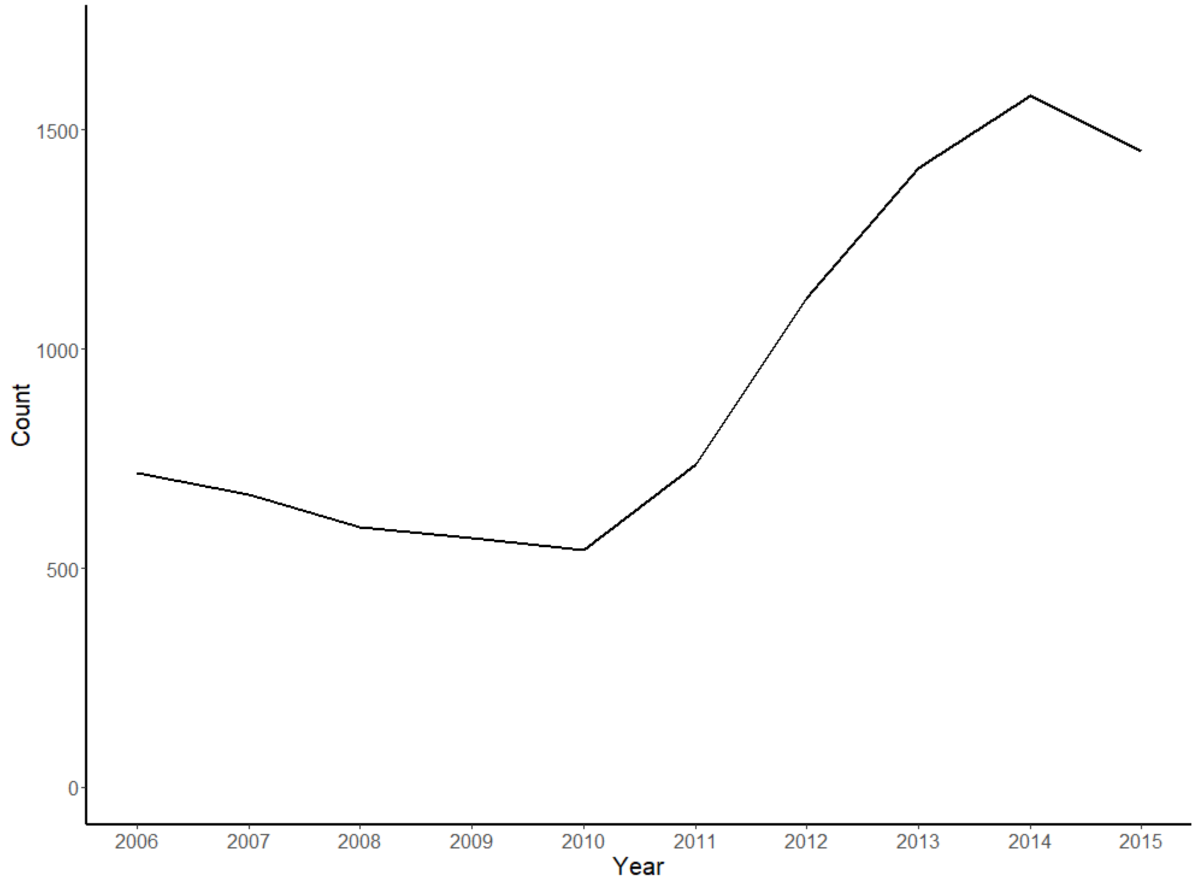
Distribution of Non-Interest Income to Gross Revenue (%) for FIs in the sample. This represents the portion of income that comes from interest income (traditional banking activities e.g. loans) and from non-interest income (e.g. fees).

Figure 3.3: Distribution of ratings



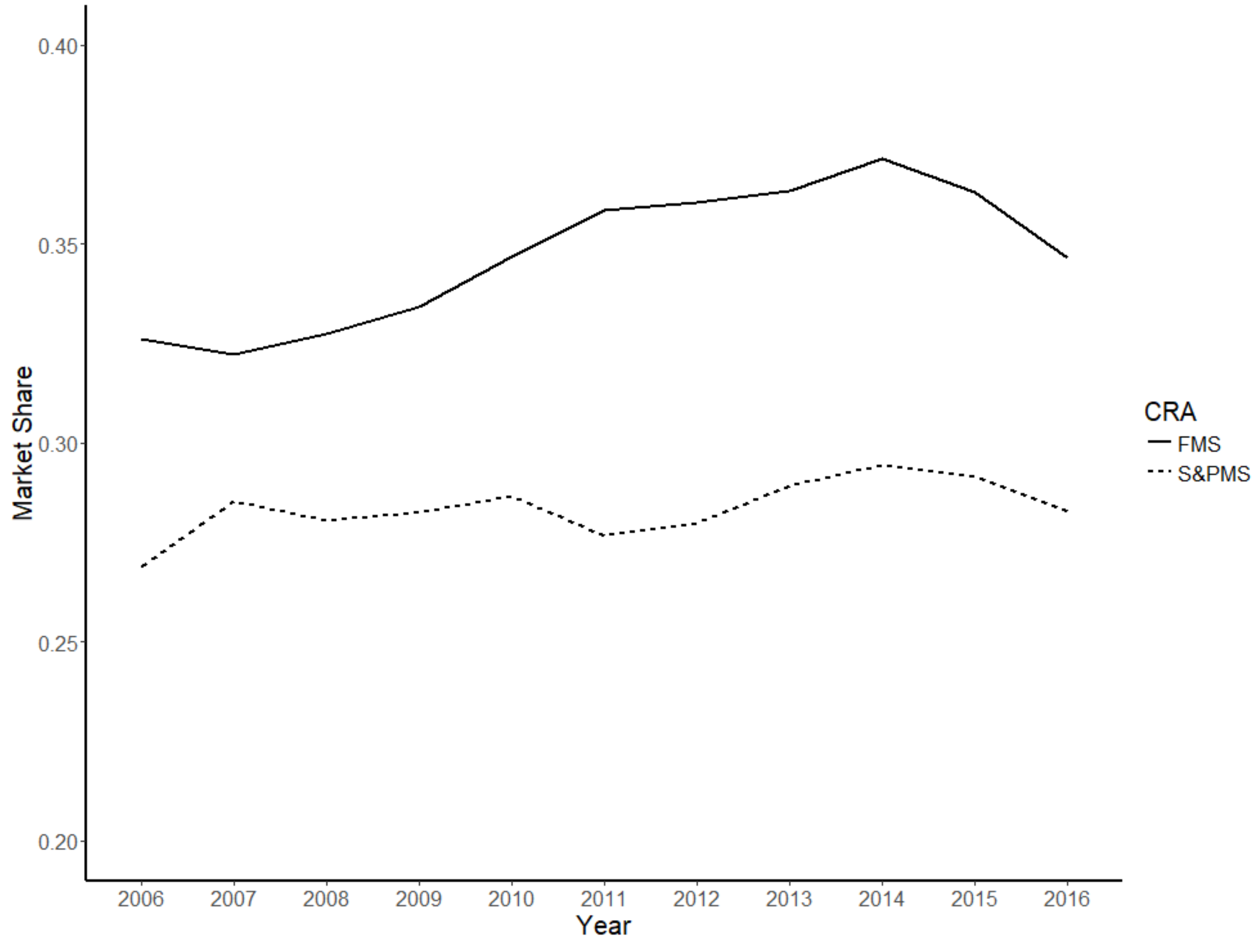
The distribution of ratings in each rating category in the EU sample from January 2006 to June 2016. The top graph shows the 18-notch scale and the lower the 52 point CCR scale.

Figure 3.4: Incidence of false warning



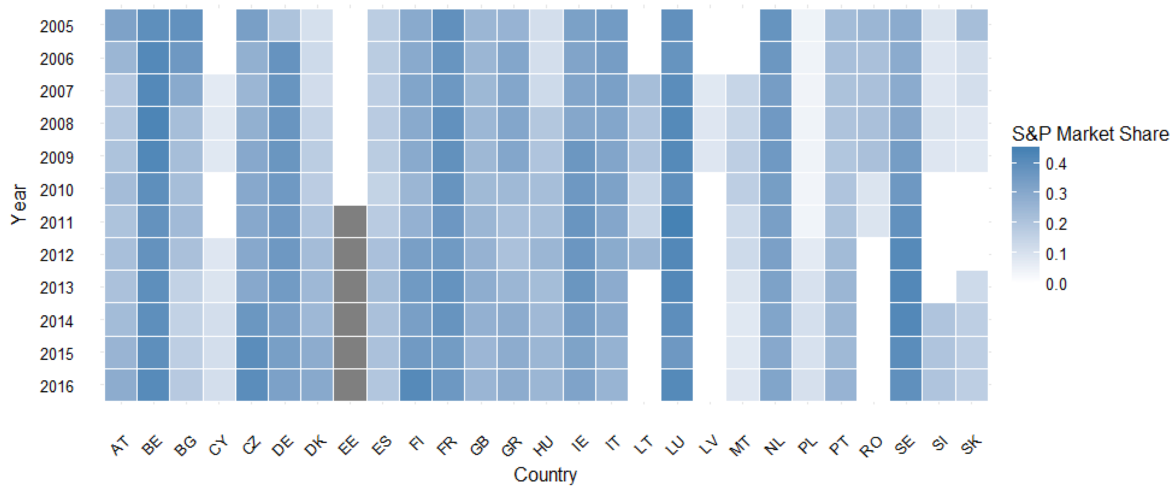
The figure displays the count of periods in which a CRA had issued a false warning to a FI from the sample of 758 rated European FIs during the period from January 2006 to June 2016 in the 27 EU countries.

Figure 3.5: S&P and Fitch market share over time



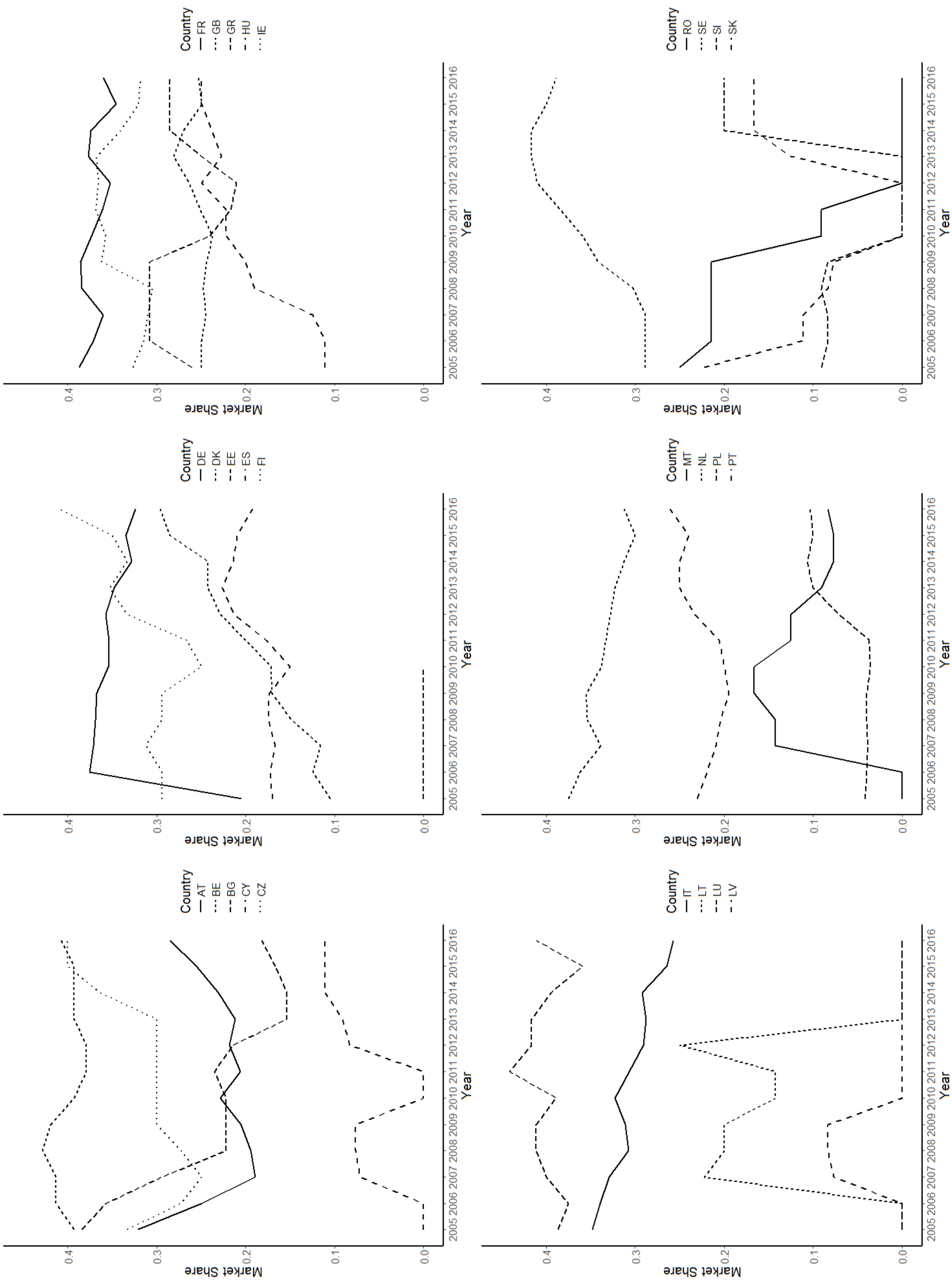
The figure displays the variation of average S&P and Fitch market share over time in the sample of 758 rated European FIs during the period from January 2006 to June 2016 in the 27 EU countries.

Figure 3.6: S&P market share distribution



Variation of S&P market share over country and year in the EU sample.

Figure 3.7: S&P market share distribution



Variation of S&P market share over country and year in the sample of 758 rated European FIs during the period from January 2006 to June 2016 in the 27 EU countries.

APPENDIX 3.I – SUPPORTING TABLES

Table A. 3.1: Rating scale and frequency

Panel A: The rating scale

S&P Rating	Moody's Rating	Fitch Rating	18-notch scale	52 point CCR scale
AAA	Aaa	AAA	18	52
AA+	Aa1	AA+	17	49
AA	Aa2	AA	16	46
AA-	Aa3	AA-	15	43
A+	A1	A+	14	40
A	A2	A	13	37
A-	A3	A-	12	34
BBB+	Baa1	BBB+	11	31
BBB	Baa2	BBB	10	28
BBB-	Baa3	BBB-	9	25
BB+	Ba1	BB+	8	22
BB	Ba2	BB	7	19
BB-	Ba3	BB-	6	16
B+	B1	B+	5	13
B	B2	B	4	10
B-	B3	B-	3	7
CCC+/CCC/CCC-	Caa1/Caa2/Caa3	CCC	2	4
CC/C/SD	Ca/C/D	CC/C/D	1	1

Panel B: Rating occurrences

S&P		Moody's		Fitch	
Rating Category	Occurrences	Rating Category	Occurrences	Rating Category	Occurrences
AAA	352	Aaa	875	AAA	456
AA+	201	Aa1	1207	AA+	545
AA	1546	Aa2	2089	AA	1549
AA-	4956	Aa3	4019	AA-	4007
A+	6650	A1	4268	A+	9678
A	5492	A2	6308	A	7298
A-	3521	A3	3777	A-	5010
BBB+	1920	Baa1	2878	BBB+	3398
BBB	1663	Baa2	2636	BBB	2557
BBB-	1269	Baa3	2496	BBB-	1761
BB+	744	Ba1	1307	BB+	1518
BB	747	Ba2	1029	BB	924
BB-	512	Ba3	1018	BB-	469
B+	233	B1	478	B+	392
B	127	B2	490	B	280
B-	76	B3	199	B-	212
CCC+	39	Caa1	107	CCC	48
CCC	51	Caa2	98	CC	4
CC	2	Caa3	75	C	0
C	0	Ca	124	RD	47
SD	24	C	0		
Total	30,125	Total	35,478	Total	40,153

Panel A shows the mapping of ratings to the 18 notch and the 52 point CCR scale. In the CCR scale positive and negative watch signals award +2/-2 points respectively and a positive and negative outlook award +1/-1 points respectively. Panel B shows the frequency of occurrences of ratings in different categories throughout the monthly EU sample.

Table A. 3.2: Rating levels - Alternative 18-notch rating scale

	Eq. (3.2)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.300***	-8.03	-0.337***	-7.68
S&PMS			-1.369*	-1.72
Post × S&PMS			-0.053	-0.39
Moody's	-0.106	-1.16	-0.269***	-3.20
Fitch	0.109	1.40		
ROAA	-0.115	-1.15	-0.061	-0.61
CIR	-0.015***	-3.43	-0.016***	-3.71
LLPNIR	-0.011***	-4.75	-0.011***	-4.47
Ln(TA)	0.241***	6.00	0.317***	7.81
NIIGR	0.008**	2.53	0.006*	1.79
ETA	-0.002	-0.11	0.008	0.36
LAtoCSTF	0.000	0.07	0.000	0.07
# Observations	105,756		75,631	
Pseudo R^2	14.38%		14.86%	

Ordered logit estimations of Eq. (3.2) and (3.3) using the 18 point rating scale (not including outlook and watch signals). Only Moody's and Fitch ratings used in Eq. (3.3). ***Post*** *start date is 1st July 2011.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and* ***country*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.3: Distribution of rating upgrades and downgrades

	CCR (outlook and watch)				Rating level only			
	Downgrades		Upgrades		Downgrades		Upgrades	
Year	#Obs	AR (%)	#Obs	AR (%)	#Obs	AR (%)	#Obs	AR (%)
2006	0		7	-0.23	0		4	-0.14
2007	37	0.23	81	-0.03	12	0.02	66	0.16
2008	105	-1.21	12	-1.99	39	-0.74	7	-0.27
2009	149	-0.97	12	0.02	97	-0.83	4	1.27
2010	97	-0.63	20	0.13	67	-0.96	3	-0.25
2011	286	-0.18	17	-0.10	206	-0.33	9	-0.32
2012	208	0.05	24	0.49	162	0.11	2	-0.21
2013	70	-0.01	20	1.26	58	0.00	5	6.80
2014	52	0.46	46	0.47	25	0.24	25	0.35
2015	83	0.63	155	0.00	57	-0.02	47	0.24
Before regulation	490	-0.60	298	-0.47	144	-0.19	88	0.11
After regulation	618	0.03	434	-0.17	286	0.12	105	0.54
Total	1108	-0.25	732	-0.29	430	0.02	193	0.34

The occurrences of rating upgrades and downgrades throughout the sample. AR is the abnormal return. The table shows both the CCR scale that takes account of changes in outlook and watch in addition to the rating and changes at the rating level only.

Table A. 3.4: Occurrences of false warnings

Country	Country code	FIs that experience false warnings	Instances of warnings	Instances of 1 year false warnings	Instances of 1.5 year false warnings	Instances of 2 year false warnings
Austria	AT	4	182	181	181	181
Belgium	BE	0	0	0	0	0
Bulgaria	BG	7	341	329	326	326
Cyprus	CY	4	230	209	209	209
Czech Republic	CZ	1	35	35	35	35
Germany	DE	1	16	10	10	10
Denmark	DK	1	9	2	2	2
Estonia	EE	0	0	0	0	0
Spain	ES	7	267	222	215	210
Finland	FI	0	0	0	0	0
France	FR	0	0	0	0	0
UK	GB	7	220	220	220	220
Greece	GR	8	402	219	169	165
Hungary	HU	4	67	64	57	55
Ireland	IE	0	0	0	0	0
Italy	IT	7	192	139	115	106
Lithuania	LT	4	337	316	309	303
Luxemburg	LU	1	36	24	17	12
Latvia	LV	7	451	438	432	426
Malta	MT	0	0	0	0	0
Netherlands	NL	1	2	2	2	2
Poland	PL	1	4	4	4	4
Portugal	PT	6	159	120	109	108
Romania	RO	3	46	35	35	35
Sweden	SE	0	0	0	0	0
Slovenia	SI	5	105	92	85	77
Slovakia	SK	1	5	5	5	5
	Total	80	3106	2666	2537	2491

The number of false warnings in each country. A warning is defined as a period in which a FI is rated BB+ or lower. A false warning is defined as a period in which is rated BB+ or below but does not default in the following 1, 1.5 or 2 years.

Table A. 3.5: Alternative definitions of false warnings

Panel A: Using B+

	Eq. (3.4)				Eq. (3.5)			
	September 2009		July 2011		September 2009		July 2011	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.272*	1.81	0.803***	2.82	0.169	1.15	1.306***	3.21
S&PMS					-4.294***	-2.81	-2.697*	-1.70
Post × S&PMS					0.318	0.81	-1.236**	-2.20
Moody's	0.132	0.38	0.133	0.38	0.725*	1.85	0.726*	1.85
Fitch	-0.614	-1.60	-0.614	-1.60				
ROAA	-0.123	-0.70	-0.124	-0.71	-0.070	-0.34	-0.071	-0.34
CIR	0.006	0.60	0.006	0.59	0.014	1.09	0.014	1.09
LLPNIR	0.015***	2.80	0.015***	2.80	0.017***	2.72	0.017***	2.72
Ln(TA)	-0.416***	-3.47	-0.417***	-3.47	-0.419***	-3.15	-0.420***	-3.15
NIIGR	0.018	1.49	0.018	1.49	0.017	1.17	0.017	1.17
ETA	0.041	0.89	0.040	0.89	0.034	0.81	0.034	0.80
LAtoCSTF	-0.011	-1.54	-0.011	-1.54	-0.008	-1.05	-0.008	-1.05
Country * Year FE	Yes		Yes		Yes		Yes	
# Observations	34,913		34,913		27,217		27,217	
Pseudo R^2	36.64%		36.71%		37.01%		37.15%	

Panel B: 2 year duration

	Eq. (3.4)				Eq. (3.5)			
	September 2009		July 2011		September 2009		July 2011	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.024	-0.42	0.376***	3.80	0.000	0.00	0.495***	4.58
S&PMS					0.925	0.70	0.714	0.53
Post × S&PMS					-0.165	-0.85	-0.358	-1.14
Moody's	0.147	0.73	0.148	0.73	0.647***	2.77	0.648***	2.77
Fitch	-0.537**	-2.45	-0.536**	-2.45				
ROAA	0.124	0.86	0.124	0.86	0.110	0.68	0.110	0.67
CIR	0.002	0.30	0.002	0.31	0.008	0.97	0.008	0.97
LLPNIR	0.013***	3.55	0.013***	3.55	0.013***	3.23	0.013***	3.23
Ln(TA)	-0.449***	-6.37	-0.450***	-6.38	-0.478***	-6.16	-0.478***	-6.17
NIIGR	-0.003	-0.63	-0.003	-0.63	0.000	0.04	0.000	0.04
ETA	-0.030	-1.02	-0.030	-1.02	-0.042	-1.28	-0.042	-1.28
LAtoCSTF	0.013***	2.67	0.013***	2.67	0.011**	2.34	0.011**	2.34
Country * Year FE	Yes		Yes		Yes		Yes	
# Observations	91,353		91,353		59,263		59,263	
Pseudo R^2	35.97%		36.00%		33.65%		33.69%	

Logit regression for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch for Eq. (3.5)). Two different regulatory start dates are included, firstly 16th September 2009 when the regulation was enacted and secondly the 1st July 2011 when ESMA was established. In panel A The dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of B+ or below does not default after one year and zero otherwise. In panel B the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after two years and zero otherwise. ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by FI and country*year interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.6: FI control variables

Indicator	Chosen Measure	Studies employed in
Asset Quality	Ratio of loan-loss provisions to net interest revenue	Sundararajan et al. (2002) Shen et al. (2012) Huang and Shen (2015) Hau et al. (2013) Poon et al. (2009) Klusak et al. (2017) Van Roy (2013) Poon and Firth (2005) Altunbas et al. (2017)
Management Efficiency	Ratio of cost to income	Shen et al. (2012) Huang and Shen (2015) Altunbas et al. (2017) Imbierowicz and Rauch (2014) Altunbas et al. (2014)
Profitability	ROA	Sundararajan et al. (2002) Shen et al. (2012) Huang and Shen (2015) Hau et al. (2013) Caporale et al. (2012) Poon et al. (2009) Klusak et al. (2017) Van Roy (2013) Poon and Firth (2005) Altunbas et al. (2017) Imbierowicz and Rauch (2014) Altunbas et al. (2014)
Revenues	Non-interest income over gross revenue	Klusak et al. (2017)
Leverage	Total assets to equity[113]	Caporale et al. (2012) Klusak et al. (2017) Van Roy (2013) Poon et al. (2009) Hau et al. (2013) Vazquez and Federico (2015)
Liquidity	Ratio of liquid assets to deposits and short-term funding	Sundararajan et al. (2002) Shen et al. (2012) Huang and Shen (2015) Caporale et al. (2012) Poon et al. (2009) Van Roy (2013) Poon and Firth (2005) Vazquez and Federico (2015) Altunbas et al. (2014)
Size	Ln(Assets)	Shen et al. (2012) Huang and Shen (2015) Hau et al. (2013) Caporale et al. (2012) Poon et al. (2009) Klusak et al. (2017) Van Roy (2013) Poon and Firth (2005) Altunbas et al. (2017) Vazquez and Federico (2015) Imbierowicz and Rauch (2014) Altunbas et al. (2014)

FI specific control variables used in Eq. (3.1), (3.2), (3.3), (3.4), (3.5), (3.7) and (3.8), all the variables vary annually.

[113] Poon et al. (2009) include the inverse of this ratio (Equity to total assets) as a measure of capital adequacy.

Table A. 3.7: EU country indices

Country	Index	Index name
Austria	ATX	Austrian Traded ATX Index
Belgium	BEL20	BEL 20 Index
Bulgaria	SOFIX	SOFIX Index
Cyprus	CYSMMAPA	General Market Index CSE
Czech Republic	PX	Prague Stock Exchange Index
Estonia	TALSE I	OMX Tallinn OMXT
Finland	HEX	OMX Helsinki Index
France	CAC	CAC 40 Index
Germany	DAX	DAX 30 Performance Index
Greece	ASE	ATHEX Composite Share PR
Hungary	BUX	Budapest Stock Exchange Index
Ireland	ISEQ	Irish Overall Index
Italy	FTSEMIB	FTSE MIB Index
Latvia	RIGSE	OMX Riga OMXR
Lithuania	VILSE	OMX Vilnius OMXV
Luxembourg	LUXXX	Luxembourg LUXX Index
Malta	MALTEX	Malta Stock Exchange IND
Netherlands	AEX	AEX-Index
Poland	WIG20	Warsaw General Index 20
Portugal	PSI20	PSI 20 Index
Romania	BET	Bucharest BET Index
Slovakia	SKSM	Slovakia SAX 16
Slovenia	SBITOP	Slovenian Blue Chip IDX
Spain	IBEX I	IBEX 35 Index
UK	UKX	FTSE 100 Index
Sweden	OMXS	OMX Stockholm (OMXS)
Denmark	OMXC	OMX Copenhagen (OMXC)

European country indices used for calculating the abnormal return.

Table A. 3.8: Informational content summary statistics

Variable	Obs	Mean	Std.	Min	Max
Rating	500,289	32.90	10.79	1	52
Abnormal return (%/100)	500,289	-0.0001	0.028	-0.652	1.911
CCR Rating change	1,538	-1.60	3.25	-20	9
CCR abnormal downgrade return	1,108	-0.002	0.043	-0.391	0.495
CCR abnormal upgrade return	430	0.0002	0.026	-0.202	0.169
Point Rating change	925	-0.857	1.258	-7	3
Point abnormal downgrade return	732	-0.003	0.044	-0.391	0.495
Point abnormal upgrade return	193	0.003	0.024	-0.062	0.169
Number of clusters	1,538	0.31	0.63	0	4
ROAA (%)	443,641	0.52	0.72	-3.38	3.45
Cost to income ratio	443,641	59.21	11.41	24.88	103.79
LLPNIR	443,641	29.66	28.32	-47.36	156.49
Ln(TA)	443,641	18.56	1.88	13.05	22.06
NII-GR	443,641	38.14	11.47	-6.03	86.02
Eq-TA	443,641	7.54	3.27	1.28	25.70
Liquid assets to deposits and STF	443,641	27.33	22.24	2.02	135.06

Summary statistics for the rating events and stock returns. There are 443,641 observations used over the period 1st January 2006 to 1st June 2016, and 1,538 rating events (including outlook and watch) and 925 (excluding outlook and watch).

Table A. 3.9: S&P market share impact

Panel A: Ordered logit - Percentage

Variable	CCR	
	Coefficient	Z-stat
S&P market share percentage (t-1)	10.286***	5.84
Controls	Yes	
Country * Year FE	Yes	
Number of observations	75,631	
Pseudo R^2	10.69%	

Panel B: Ordered probit

Variable	Moody's and Fitch		Moody's		Fitch	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
S&PMS	-0.899***	-6.12	-0.624***	-4.89	-0.746***	-3.33
Controls	Yes		Yes		Yes	
Country * Year FE	Yes		Yes		Yes	
Number of observations	75,631		35,478		40,153	
Pseudo R^2	10.0%		11.5%		12.2%	

Panel C: Ordered logit – No fixed effects

Variable	Moody's and Fitch		Moody's		Fitch	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
S&PMS	-0.829***	-4.66	-0.372**	-1.97	-1.246***	-5.39
Controls	Yes		Yes		Yes	
Country * Year FE	No		No		No	
Number of observations	75,631		35,478		40,153	
Pseudo R^2	3.87%		5.27%		3.83%	

Panel D: Ordered logit – In post regulatory period

Variable	Post = 1	
	Coefficient	Z-stat
S&PMS	-1.609**	-2.36
Controls	Yes	
Country * Year FE	Yes	
Number of observations	44,060	
Pseudo R^2	11.72	

Panel E: Ordered logit - Alternative cut-offs

Variable	10%		40%	
	Coefficient	Z-stat	Coefficient	Z-stat
S&PMS	-2.669***	-9.46	-1.592***	-5.84
Moody's	-0.519***	-5.27	-0.519***	-5.27
Controls	Yes		Yes	
Country * Year FE	Yes		Yes	
Number of observations	75,631		75,631	
Pseudo R^2	10.69%		10.69%	

*Regression models of Eq. (3.1). Unless specified the regression includes ratings from Moody's and Fitch. In Panel A the percentage S&P market share is employed. In Panels B, C and D the **S&PMS** is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. It is employed on a country and year basis. In Panel E alternative cut-offs between countries of stronger and weaker reputational concerns, using the limits of 10% and 40% are used instead (dummy, 1 in lower 10%/40%, 0 in top 90%/60%, lagged by 1 year). The dependent variable in each panel is the FI credit rating (52 point CCR scale) in the EU sample during the period 2006 to 2016. Standard errors are clustered by FI and **country*year** interactions are included and ***, **, * represent significance beyond the 1^{st}, 5^{th} and 10^{th} percentile levels respectively.*

Table A. 3.10: OLS and ordered probit models

Panel A: Rating levels

	Eq. (3.2)				Eq. (3.3)			
	Ordered Probit		OLS		Ordered Probit		OLS	
Variable	Coefficient	Z-stat	Coefficient	t-stat	Coefficient	Z-stat	Coefficient	t-stat
Post	-0.159***	-8.42	-1.062***	-8.69	-0.178***	-8.48	-1.186***	-8.38
S&PMS					-0.690	-1.45	-3.581	-1.13
Post × S&PMS					-0.032	-0.45	-0.443	-0.81
Moody's	-0.019	-0.36	-0.363	-1.13	-0.266***	-5.38	-2.020***	-6.56
Fitch	0.213***	4.50	1.479***	5.22				
ROAA	-0.069	-1.30	-0.227	-0.69	-0.048	-0.87	-0.108	-0.31
CIR	-0.007***	-3.14	-0.039***	-2.80	-0.009***	-3.59	-0.047***	-3.24
LLPNIR	-0.005***	-4.36	-0.034***	-4.43	-0.006***	-4.15	-0.036***	-4.19
Ln(TA)	0.125***	5.80	0.761***	6.07	0.171***	7.84	1.016***	7.90
NIIGR	0.003**	1.96	0.017	1.62	0.002	1.22	0.010	0.83
ETA	-0.001	-0.09	-0.015	-0.20	0.004	0.30	0.019	0.26
LAtoCSTF	0.000	0.26	-0.002	-0.20	0.001	0.52	0.001	0.07
Country * Year FE	Yes		Yes		Yes		Yes	
# Observations	105,756		105,756		75,631		75,631	
Pseudo R^2	9.53%		51.85%		9.99%		52.47%	

Panel B: False warnings

	Eq. (3.4)				Eq. (3.5)			
	Probit		OLS		Probit		OLS	
Variable	Coefficient	Z-stat	Coefficient	t-stat	Coefficient	Z-stat	Coefficient	t-stat
Post	0.204***	3.95	0.019***	3.51	0.251***	4.38	0.024***	3.88
S&PMS					0.170	0.26	-0.062	-1.09
Post × S&PMS					-0.012	-0.08	0.019	0.71
Moody's	0.113	1.10	0.019*	1.74	0.371***	3.08	0.041***	3.35
Fitch	-0.264**	-2.42	-0.021**	-2.01				
ROAA	0.014	0.20	-0.006	-0.52	0.005	0.06	-0.007	-0.51
CIR	-0.001	-0.32	0.000	-0.06	0.002	0.41	0.000	0.67
LLPNIR	0.006***	3.32	0.001***	2.57	0.006***	2.95	0.001**	2.38
Ln(TA)	-0.222***	-6.48	-0.019***	-5.33	-0.242***	-6.29	-0.022***	-5.26
NIIGR	0.000	-0.12	0.000	-0.01	0.002	0.53	0.000	0.50
ETA	-0.008	-0.50	-0.001	-0.48	-0.014	-0.82	-0.002	-0.90
LAtoCSTF	0.006***	2.65	0.001***	2.79	0.006**	2.21	0.001**	2.50
Country * Year FE	Yes		Yes		Yes		Yes	
# Observations	91,353		105,756		59,263		75,631	
Pseudo R^2	36.70%		34.88%		34.08%		34.60%	

Ordered probit and OLS estimations of Eq. (3.2) and Eq. (3.3) and probit and OLS estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. The start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale. In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.11: Country and year separately, no interactions

Panel A: Rating levels

	Eq. (3.2)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.237***	-9.55	-0.297***	-8.17
S&PMS			0.445**	2.23
Post × S&PMS			0.212	0.96
Moody's	0.011	0.12	-0.466***	-5.90
Fitch	0.415***	5.36		
ROAA	-0.072	-0.84	-0.007	-0.08
CIR	-0.017***	-4.43	-0.018***	-4.57
LLPNIR	-0.016***	-7.69	-0.015***	-6.90
Ln(TA)	0.219***	5.83	0.297***	7.90
NIIGR	0.007**	2.29	0.005	1.59
ETA	0.000	0.01	0.005	0.25
LAtoCSTF	-0.001	-0.20	-0.000	-0.17
Country FE	Yes		Yes	
Year FE	Yes		Yes	
# Observations	105,756		75,631	
Pseudo R^2	8.48%		9.22%	

Panel B: False warnings

	Eq. (3.4)		Eq. (3.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.414***	3.72	0.536***	4.16
S&PMS			-0.765**	-1.96
Post × S&PMS			-0.303	-0.72
Moody's	0.157	0.85	0.636***	2.99
Fitch	-0.500**	-2.47		
ROAA	0.071	0.57	0.017	0.12
CIR	0.004	0.54	0.007	1.04
LLPNIR	0.013***	4.19	0.013***	3.89
Ln(TA)	-0.392***	-6.38	-0.439***	-6.29
NIIGR	0.000	0.06	0.004	0.59
ETA	-0.025	-0.93	-0.035	-1.20
LAtoCSTF	0.009**	2.07	0.008*	1.91
Country FE	Yes		Yes	
Year FE	Yes		Yes	
# Observations	101,883		73,126	
Pseudo R^2	34.57%		35.25%	

Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). ***Post*** *start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale. In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.12: No fixed effects

Panel A: Rating levels

	Eq. (3.2)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.951***	-11.70	-1.039***	-12.29
S&PMS			-0.767***	-3.79
Post × S&PMS			-0.060	-0.27
Moody's	-0.284***	-2.92	-0.483***	-6.07
Fitch	0.131	1.59		
ROAA	-0.359***	-3.76	-0.262**	-2.55
CIR	-0.016***	-4.34	-0.018***	-4.77
LLPNIR	-0.025***	-11.27	-0.024***	-10.85
Ln(TA)	0.161***	3.99	0.276***	6.95
NIIGR	0.003	1.10	0.004	1.18
ETA	-0.048**	-2.36	-0.027	-1.36
LAtoCSTF	0.003	1.33	0.003	1.31
Country FE	No		No	
Year FE	No		No	
# Observations	105,756		75,631	
Pseudo R^2	3.70%		5.00%	

Panel B: False warnings

	Eq. (3.4)		Eq. (3.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	1.245***	8.89	1.304***	8.14
S&PMS			1.109***	3.40
Post × S&PMS			-0.317	-0.94
Moody's	0.677***	3.58	0.679***	3.59
Fitch	0.090	0.48		
ROAA	0.329**	2.42	0.233*	1.73
CIR	0.007	1.27	0.011*	1.83
LLPNIR	0.023***	8.47	0.021***	7.46
Ln(TA)	-0.323***	-6.73	-0.390***	-7.51
NIIGR	0.006	1.19	0.005	1.04
ETA	0.009	0.41	-0.008	-0.33
LAtoCSTF	0.007*	1.68	0.007*	1.66
Country FE	No		No	
Year FE	No		No	
# Observations	105,756		75,631	
Pseudo R^2	15.50%		18.40%	

Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). ***Post*** *start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale. In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.13: Alternative S&PMS cut-offs

Panel A: Rating levels

Variable	10% Coefficient	10% Z-stat	40% Coefficient	40% Z-stat
Post	-0.351***	-8.33	-0.349***	-7.06
S&PMS	-1.193*	-1.69	-1.238	-1.33
Post × S&PMS	-1.127***	-4.04	-0.006	-0.07
Moody's	-0.520***	-6.25	-0.520***	-6.25
ROAA	-0.030	-0.30	-0.030	-0.30
CIR	-0.017***	-3.89	-0.017***	-3.89
LLPNIR	-0.011***	-4.46	-0.011***	-4.46
Ln(TA)	0.302***	7.56	0.302***	7.56
NIIGR	0.006*	1.69	0.006*	1.69
ETA	0.006	0.29	0.006	0.29
LAtoCSTF	0.000	0.03	0.000	0.03
Country * Year FE	Yes		Yes	
# Observations	75,631		75,631	
Pseudo R^2	10.70%		10.70%	

Panel B: False warnings

Variable	10% Coefficient	10% Z-stat	40% Coefficient	40% Z-stat
Post	0.459***	4.35	0.528***	3.47
S&PMS	1.409	0.93	1.983	1.33
Post × S&PMS	0.789	0.61	-0.188	-1.01
Moody's	0.682***	2.95	0.682***	2.95
ROAA	0.048	0.29	0.048	0.29
CIR	0.006	0.82	0.006	0.82
LLPNIR	0.012***	2.96	0.012***	2.97
Ln(TA)	-0.466***	-6.11	-0.466***	-6.11
NIIGR	0.002	0.29	0.002	0.29
ETA	-0.038	-1.16	-0.038	-1.16
LAtoCSTF	0.010**	2.02	0.010**	2.03
Country * Year FE	Yes		Yes	
# Observations	59,263		59,263	
Pseudo R^2	34.14%		34.14%	

*Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). Post start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale. In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. Alternative levels of S&P market share of 10% and 40% have been used instead of the original 25% as a robustness test (**S&PMS** is a dummy, 1 in lower 10%/40%, 0 in top 90%/60%, lagged by 1 year). Standard errors are clustered by company and **country*year** interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.14: False warnings – Negative coverage ratio

	Eq. (3.4)	
Variable	Coefficient	Z-stat
Post	0.361***	3.45
Moody's	0.176	0.89
Fitch	-0.553**	-2.53
ROAA	0.010	0.07
CIR	0.001	0.10
LLPNIR	0.011***	3.15
Ln(TA)	-0.403***	-5.99
NIIGR	-0.003	-0.44
ETA	-0.018	-0.64
LAtoCSTF	0.011**	2.40
# Observations	91,032	
Pseudo R^2	36.35%	

The alternative case (ii) for evaluating the coverage ratio. In this case the 12 FIs that lacked information regarding their coverage ratio are assumed to have a negative coverage ratio. EU sample which includes ratings by S&P, Moody's and Fitch. ***Post*** *starts after the 1st July 2011 and the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. Standard errors are clustered by company and* ***country*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.15: Informational content – Clustered vs independent events

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic	Welch t-statistic
Credit rating downgrades	Whole sample	#Obs	490	618			
		Mean return (%)	-0.597***	0.027	-0.624**	-2.39	-2.34
	Independent events	#Obs	355	451			
		Mean return (%)	-0.667***	0.084	-0.751**	-2.50	-2.48
	Clustered events	#Obs	135	167			
		Mean return (%)	-0.415	-0.129	-0.286	-0.54	-0.52
Credit rating upgrades	Whole sample	#Obs	144	286			
		Mean return (%)	-0.186	0.120	-0.307	-1.15	-1.16
	Independent events	#Obs	124	235			
		Mean return (%)	0.084	0.149	-0.065	-0.24	-0.27
	Clustered events	#Obs	20	51			
		Mean return (%)	-1.863	-0.010	-1.853**	-2.21	-1.60

Stock market reaction (mean abnormal return) to rating announcements throughout the European sample during the period 1st January 2006 to 1st June 2016. The sample compares rating announcements before and after the introduction of the regulation and distinguishes between independent and clustered events. ***Post*** *is defined as the 1st July 2011 when ESMA was established. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.16: Informational content – Separate CRAs

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic	Welch t-statistic
Credit rating downgrades	S&P	#Obs	186	212			
		Mean return (%)	-0.601	-0.041	-0.561	-1.20	-1.17
	Moody's	#Obs	162	217			
		Mean return (%)	-0.349	-0.160	-0.189	-0.56	-0.53
	Fitch	#Obs	142	189			
		Mean return (%)	-0.875**	0.317	-1.192**	-2.18	-2.19
Credit rating upgrades	S&P	#Obs	51	91			
		Mean return (%)	-0.575	0.419**	-0.994**	-2.13	-1.83
	Moody's	#Obs	52	139			
		Mean return (%)	0.232	-0.376*	0.608*	1.66	2.17
	Fitch	#Obs	41	56			
		Mean return (%)	-0.233	0.868*	-1.101*	-1.75	-1.89

Stock market reaction (mean abnormal return) to rating announcements throughout the European sample during the period 1st January 2006 to 1st June 2016. The sample compares rating announcements before and after the introduction of the regulation separately for each CRA. ***Post*** *is defined as the 1st July 2011 when ESMA was established. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.17: Information content – OLS Eq. (3.8) – S&P market share

	Rating Downgrades		Rating Upgrades	
Variable	Coefficient	t-stat	Coefficient	t-stat
Post	-0.057*	-1.83	-0.058*	-1.81
Rating Downgrade	-0.540*	-1.78		
Rating Upgrade			-0.101	-0.77
S&PMS	0.097***	2.62	0.098***	2.61
Rating Downgrade × S&PMS	0.604	1.09		
Rating Upgrade × S&PMS			-0.347*	-1.66
Post × S&PMS	0.050	1.04	0.050	1.03
Post × Rating Downgrade	0.328	0.99		
Post × Rating Upgrade			0.482**	2.17
Post × Rating Downgrade × S&PMS	-0.321	-0.51		
Post × Rating Upgrade × S&PMS			-0.365	-1.10
Moody's	-0.015	-1.34	-0.013	-1.16
Fitch	-0.007	-0.52	-0.004	-0.29
ROAA	0.073	0.93	0.074	0.94
CIR	0.007*	1.93	0.007*	1.93
LLPNIR	0.003	0.93	0.003	0.92
Ln(TA)	0.014	0.94	0.014	0.95
NIIGR	0.003	1.19	0.003	1.22
ETA	-0.008	-0.78	-0.008	-0.79
LAtoCSTF	-0.004**	-2.47	-0.004**	-2.48
Country * Year FE	Yes		Yes	
# Observations	443,641		443,641	
Pseudo R^2	0.001%		0.001%	

Post is a dummy variable 1 after 1st July 2011 and zero otherwise. OLS regression of abnormal returns for the EU sample which includes ratings by S&P, Moody's and Fitch. Post, rating downgrade, upgrade and the interactions are multiplied by 100 to give the impact on the percentage abnormal return. All the control variable coefficients are multiplied by 1000 for readability (Moody's and below in the table). ***Rating upgrade*** *and* ***downgrade*** *are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Only cases with the full window [-230, -30] are considered. Standard errors are clustered by company and* ***country*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.18: Event study – Excluding outlook and watch

Panel A: September 2009

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic	Welch t-statistic
Credit rating downgrades	Whole sample	#Obs	272	836			
		Mean return (%)	-0.938***	-0.025	-0.913***	-3.03	-2.45
	Moody's and Fitch	#Obs	153	557			
		Mean return (%)	-0.885**	-0.036	-0.848**	-2.26	-1.84
Credit rating upgrades	Whole sample	#Obs	109	321			
		Mean return (%)	-0.260	0.112	-0.372	-1.28	-1.23
	Moody's and Fitch	#Obs	72	216			
		Mean return (%)	0.079	-0.032	0.111	0.31	0.40

Panel B: July 2011

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic	Welch t-statistic
Credit rating downgrades	Whole sample	#Obs	298	434			
		Mean return (%)	-0.470*	-0.166	-0.304	-0.92	-0.89
	Moody's and Fitch	#Obs	207	297			
		Mean return (%)	-0.649**	-0.223	-0.426	-1.12	-1.09
Credit rating upgrades	Whole sample	#Obs	88	105			
		Mean return (%)	0.107	0.538*	-0.430	-1.26	-1.33
	Moody's and Fitch	#Obs	65	81			
		Mean return (%)	0.126	0.541	-0.415	-0.95	-1.02

Panel C: May 2013

Upgrade/downgrade	Sample	Variable	Post2 = 0	Post2 = 1	Difference (Before-After)	T-statistic	Welch t-statistic
Credit rating downgrades	Whole sample	#Obs	904	204			
		Mean return (%)	-0.460***	0.686**	-1.146***	-3.43	-3.14
	Moody's and Fitch	#Obs	575	135			
		Mean return (%)	-0.431***	0.684	-1.115***	-2.84	-2.29
Credit rating upgrades	Whole sample	#Obs	180	250			
		Mean return (%)	0.037	0.004	0.033	0.13	0.12
	Moody's and Fitch	#Obs	121	267			
		Mean return (%)	0.272	-0.204	0.476	1.55	1.49

The Table presents the results of the event study for the stock market reaction (abnormal return) to credit rating signals (excluding outlook and watch) for the sample of 758 rated European FIs during the period January 2006 to June 2016 in the 27 EU countries. ***Post*** *is defined as the September 2009/July 2011/May 2013 in Panel A, B and C respectively. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table A. 3.19: No PIIGS countries

Panel A: Rating levels

	Eq. (3.2)		Eq. (3.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.141***	-6.58	-0.167***	-6.74
S&PMS			-1.351*	-1.81
Post × S&PMS			-0.205*	-1.76
Moody's	-0.212*	-1.85	-0.585***	-5.45
Fitch	0.263***	2.69		
ROAA	-0.127	-1.10	-0.030	-0.26
CIR	-0.011**	-2.05	-0.013**	-2.54
LLPNIR	-0.009***	-3.46	-0.009***	-2.81
Ln(TA)	0.162***	3.45	0.251***	5.37
NIIGR	0.008**	2.28	0.005	1.42
ETA	-0.014	-0.55	-0.004	-0.17
LAtoCSTF	-0.001	-0.21	-0.000	-0.09
Country * Year FE	Yes		Yes	
# Observations	75,122		53,359	
Pseudo R^2	8.30%		9.30%	

Panel B: False warnings

	Eq. (3.4)		Eq. (3.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.264***	2.91	0.346***	3.17
S&PMS			0.742	0.54
Post × S&PMS			0.100	0.36
Moody's	0.267	0.80	0.712**	2.12
Fitch	-0.439	-1.36		
ROAA	0.052	0.30	0.055	0.26
CIR	-0.009	-0.73	0.004	0.30
LLPNIR	0.012**	2.27	0.014**	2.14
Ln(TA)	-0.532***	-5.26	-0.580***	-5.02
NIIGR	-0.003	-0.37	-0.000	-0.05
ETA	0.000	0.01	-0.014	-0.32
LAtoCSTF	0.018***	2.79	0.014**	2.37
Country * Year FE	Yes		Yes	
# Observations	62,993		38,677	
Pseudo R^2	40.70%		38.70%	

Ordered logit estimation of Eq. (3.2) and Eq. (3.3) and logit estimation of Eq. (3.4) and Eq. (3.5) for the EU sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (3.3) and Eq. (3.5)). ***Post*** *start date is 1st July 2011. In Eq. (3.2) and Eq. (3.3) the dependent variable is credit rating (on a 52 point CCR scale. In Eq. (3.4) and Eq. (3.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. PIIGS countries are excluded.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 3.20: Informational content September – No PIIGS countries

Variable	Eq. (3.7)				Eq. (3.8)			
	Rating Downgrades		Rating Upgrades		Rating Downgrades		Rating Upgrades	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.051*	-1.83	-0.051*	-1.81	-0.057*	-1.83	-0.058*	-1.81
Rating Downgrade	-4.829*	-1.72			-5.404*	-1.78		
Rating Upgrade			-1.341	-1.12			-1.009	-0.77
S&PMS					0.971**	2.62	0.975**	2.61
Rating Downgrade × S&PMS					0.604	1.09		
Rating Upgrade × S&PMS							-0.347	-1.66
Post × S&PMS					0.498	1.04	0.497	1.03
Post × Rating Downgrade	2.990	0.98			3.282	0.99		
Post × Rating Upgrade			0.445**	2.20			0.482**	2.17
Post × Rating Downgrade × S&PMS					-3.208	-0.51		
Post × Rating Upgrade × S&PMS							-3.647	-1.10
Moody's	-0.015	-1.36	-0.013	-1.19	-0.015	-1.34	-0.013	-1.16
Fitch	-0.006	-0.50	-0.004	-0.29	-0.007	-0.52	-0.004	-0.29
ROAA	0.073	0.93	0.073	0.94	0.073	0.93	0.073	0.94
CIR	0.007*	1.93	0.007*	1.93	0.007*	1.93	0.007*	1.93
LLPNIR	0.003	0.93	0.003	0.92	0.003	0.93	0.003	0.92
Ln(TA)	0.014	0.94	0.014	0.95	0.014	0.94	0.014	0.95
NIIGR	0.003	1.21	0.003	1.22	0.003	1.19	0.003	1.22
ETA	-0.008	-0.79	-0.008	-0.78	-0.008	-0.78	-0.008	-0.79
LAtoCSTF	-0.004**	-2.47	-0.004**	-2.48	-0.004**	-2.47	-0.004**	-2.48
Country * Year FE	Yes		Yes		Yes		Yes	
# Observations	443,641		443,641		443,641		443,641	
Adjusted R^2	0.001%		0.001%		0.001%		0.001%	

Post *is a dummy variable 1 after 1st July 2011 and zero otherwise. OLS regression of abnormal returns for the EU sample which includes ratings by S&P, Moody's and Fitch. PIIGS countries are excluded. Post, rating downgrade, upgrade and the interactions are multiplied by 100 to give the impact on the percentage abnormal return. All the control variable coefficients are multiplied by 1000 for readability (Moody's and below in the table).* ***Rating upgrade*** *and* ***downgrade*** *are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise.* ***S&PMS*** *is the S&P market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Only cases with the full window [-230, -30] are considered. Standard errors are clustered by company and* ***country*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Regulating rating agencies in the US: A story of three agencies

Chapter 4

4.1 INTRODUCTION

The 2008 financial crisis caused increased scrutiny of the activities of credit rating agencies (CRAs), the quality of their ratings and the role they play in financial markets. The role that rating inflation played in the lead up to, and during, the 2008 financial crisis has been widely criticized, as the widespread over ratings of many structured financial products (RMBs, CDOs etc) and the financial institutions (FIs) that handled them was one of the key causes of the crisis in the US. To reform the industry and to prevent a reoccurrence, US regulators published the Dodd-Frank act (DFA) in July 2010 (see Section 2.3.3). This act brought into effect wide sweeping reforms, many of which were targeted at CRAs, in an effort to improve rating quality through increased disclosure requirements and making CRAs increasingly accountable for their ratings. The aim of this Chapter is to investigate whether the US regulation, the DFA, achieved its goal of increasing rating quality

The quality of ratings is vital for the efficient functioning of financial markets, as ratings are used to provide new information regarding an issuer's creditworthiness to the market. Inaccurate or inflated ratings can mislead market participants as to the true financial state of a financial institution, which was observed multiple times during the 2008 financial crisis.[114] Additionally, many pieces of regulation rely on credit ratings e.g. the use of FI ratings in calculating the capital requirement sin the Basel Accords. It is crucial that regulators ensure that CRAs accurately capture the current financial situation of the institutions they rate. However, evidence in the EU (see Chapter 3) and US corporate rating market (see Dimitrov et al., 2015) indicate that rating reforms are not going as expected. This emphasises the need to understand if and how the regulation has affected FI ratings.

To examine the impact of the CRA regulation, a sample of 454 FIs in the US rated by the big three CRAs, S&P, Moody's and Fitch during the period January 2005 to June 2016 is employed (see Section 4.3). As in Chapter 3, this Chapter examine three hypotheses that explain how the US regulatory reforms affect credit ratings of US FIs; namely: *disciplining*, *conservatism* and *reputation hypothesis*.

Firstly, *disciplining hypothesis* states that the regulation succeeds in the objective of increasing rating quality as the increased legal and regulatory repercussions will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring (Bae et al.,

[114] E.g. Lehman Brothers held a AAA rating mere months before their collapse.

2015; Dimitrov et al., 2015). The US CRA regulation also promotes the disclosure of conflicts of interests, strengthening of internal control structures and increased transparency, which will contribute to increased rating quality and prevent potential causes of rating inflation. Secondly, *rating conservatism* argues that CRAs expose themselves to greater scrutiny, fines and potential liability by over-rating (less conservative) than under rating (more conservative) (Bannier et al., 2010). As a result, if scrutiny, fines and a CRAs liability for its ratings increase, this will cause a CRA to shift to more conservative rating behaviour to avoid the increased repercussions of over rating. The resultant shift to lower ratings will then not be due to more accurate ratings or a reduction in rating inflation, but rather due to an unjustifiable decrease in ratings to avoid the increased repercussions.[115] Significantly, this effect should only vary with increased regulatory stringency (i.e. the regulation) and opacity and not vary with reputational concerns.[116] Lastly, *reputation hypothesis* states that CRAs may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FIs financial characteristics to protect and rebuild their reputation. Crucially, if *reputation hypothesis* presents, its effect should be stronger in markets where CRAs care more about their reputation, i.e. stronger reputational concerns, as they will go to greater lengths to protect their reputation in such markets (Becker and Milbourn, 2011).

This Chapter tests for the presence of the three hypotheses in the post-DFA period. Each hypothesis produces three empirical testable predictions. *Disciplining hypothesis* predicts that in the post regulatory period: (i) CRAs issue lower ratings, (ii) no increase in false warnings, (iii) credit rating upgrades should become more informative and (iv) downgrades should become more informative. *Rating conservatism* predicts: (i) CRAs issue lower ratings, (ii) an increase in false warnings, (iii) credit rating upgrades should potentially more informative and (iv) downgrades should become less informative. *Reputation hypothesis* predicts that in the post regulatory period: (i) CRAs issue lower ratings, (ii) an increase in false warnings and (iii) credit rating upgrades are potentially more informative and (iv) while downgrades are less informative. Crucially the effects of *reputation hypothesis* will vary with the strength of

[115] As in Chapter 3, FIs provide a good setting for which to measure this conservative bias, as it should be stronger for more opaque firms (Bannier et al., 2010) and FIs are more opaque than corporates (Flannery et al., 2013; Iannotta, 2006; Morgan, 2002).

[116] Opacity should not increase during our sample, if anything the DFA acts to increase transparency and hence lessen any potential conservative bias.

reputational concerns, which can be measured with the use of Fitch market share[117] as a proxy (see Section 4.3.3).

This Chapter contributes by furthering the understanding of how passage of the DFA has impacted the FI rating sector. Previously, the literature (see Section 4.1 and Section 2.3.5) has focused on how the reforms of CRAs have impacted the US corporate rating market. During the 2008 financial crisis, it was financial institutions and not corporates that were at the heart of the rating issues and as such they warrant significant investigation to ensure that the reforms have successfully improve the quality of FI ratings in the US.

This Chapter's results contrast with those reported for the EU FI rating market (see Chapter 3), where increased *rating conservatism* is driving the changes and the US corporate rating market where *reputation hypothesis* dominates. The results of this Chapter (see Section 4.5) reveal that when the FI rating market as a whole is considered, the passage of the DFA has no significant impact on rating levels or the frequency of false warnings. Each CRA reacts to the US regulation in a different manner. Moody's reacts by lowering rating justifiably as there is no corresponding increase in false warnings, indicating that the regulation has led to a reform in Moody's rating practices and methodology and potentially eliminating rating inflation (*disciplining hypothesis*). S&P FI rating is not affected by the passage of the DFA, with no changes in S&P FI rating levels in the post regulatory period and no change in the incidence of false warnings. Lastly, there is an increase in Fitch FI rating levels in the DFA period, potentially caused by the elimination of a pre-DFA conservative bias.

The results show no support for *rating conservatism* in the US FI rating market as there was no fall in rating levels and corresponding increase in false warnings. This is not entirely unexpected as the SEC has been much less active than its European counterpart ESMA in enforcing the regulation and has issued far fewer fines (see Section 2.3.2). The lack of intervention from the SEC has contributed to the lack of a conservative bias.[118] Additionally, there is no evidence for *reputation hypothesis* given the lack of any variation in the effect of the DFA regulation between states with greater and lesser reputational concerns (see Section 4.5.1).

---

[117] Both Becker and Milbourn (2011) and Dimitrov et al. (2015) employ Fitch market share because they are examining corporates in the US where Fitch has a much weaker presence (see Section 4.3.3).

[118] In the US the SEC previously oversaw CRA, while in the EU ESMA was a newly established regulatory body. The uncertainty with how strongly ESMA would enforce the regulation would potentially add to the conservative bias present in the EU. However, in the US CRAs have experience dealing with the SEC and there would be much less uncertainty about how strongly the regulation would be enforced. This perhaps contributes to the lack of a conservative rating bias.

Lastly, a reduction in stock market reaction to rating announcements, particularly rating downgrades is evident in the post regulatory period (see Section 4.5.3). Both the combined sample and each CRA separately exhibit a reduction in the market reaction to rating downgrades. The lack of evidence to support the presence of increased *rating conservatism,* suggests that the market is placing less importance upon ratings.

The Chapter is set as follows. Section 4.1 reviews the literature and prior research on the impact of US efforts to regulate CRAs. Section 4.3 describes the data and variables used. Section 4.4 explains the model and methodology. Section 4.5 presents the empirical results, Section 4.6 compares the EU and US regulatory impacts and Section 4.7 concludes.

4.2 LITERATURE REVIEW

As discussed in Chapter 3, Section 3.2, most CRAs employ the "issuer pays" model, whereby the issuer (financial institution) is required to purchase the rating. Issuers preference for favourable rather than accurate ratings has led to conflict of interest and ratings shopping (Boylan, 2012; Bolton et al., 2012, see Chapter 2 Section 2.2.1) and the counter force of CRA reputation and "reputational capital" (Flynn and Ghent, 2017; Lugo at al., 2015; Coffee, 2011, see Chapter 2 Section 2.2.3).

The US rating industry, likes the EU, is dominated by a relatively small number of CRAs and hence the competition is limited principally to the three dominant CRAs (S&P, Moody's and Fitch).[119] As discussed in Chapter 2, Section 2.2.3, competition has significant (Becker and Milbourn, 2011; Morkoetter et al., 2017; Flynn and Ghent, 2017) impact on the behaviour of CRAs and the quality of their ratings. The conclusion in the literature is that increased competition can promote "rating inflation", whereby a CRA may inflate or exaggerate a rating in order to attract, or maintain, business from issuers. This has been shown to be the case in the US corporate bond market (Becker and Milbourn, 2011; Dimitrov et al., 2015) and in the US structured finance market (Flynn and Ghent, 2017).

The oligopolistic nature of the ratings market and the issuer pays model are unlikely to change (Dang and Felgenhauer, 2012, see Section 2.2.3). Dang and Felgenhauer (2012) show that it is socially more efficient for issuers to pay for ratings (issuer pays model) than having traders pay for the rating reports. They show that a trader has a strong incentive to obtain information from the same source as other traders, which then incentive incumbent CRAs to prevent new market entrants from establishing customer bases by subsidizing unsolicited rating reports and providing them for free. Dang and Felgenhauer (2012) find that if the information provided is considered precise enough, then there is little to no demand for further (even free) information.

The issue of conservative rating behaviour has not been explored in the literature. The issue arises as CRAs are not equally penalised for over rating (rating too high) vs under rating (rating too low). A rating that is too high and subsequently defaults is much more likely to incur scrutiny or penalties from a regulatory and anger and civil cases from market participants

[119] The big three CRA companies, in the US, also provide the ratings for; 87.8% of financial institutions, 60.7% of insurance companies, 89.2% of corporate issuers, 87.5% of asset-backed securities and 99.1% of government securities (SEC, 2017).

(Bannier et al., 2010). As a result, heightened penalties or increased uncertainty about an issuer[120] can increase this bias and cause CRAs to lower their ratings unjustifiably. FIs are much more informationally opaque (Flannery et al., 2013; Iannotta, 2006; Morgan, 2002)[121] and hence create more uncertainty for CRAs and potentially expose them to fines. The literature is currently silent on how increased regulatory stringency, fines and liability can impact the level of conservatism in the rating industry. Due to the increased informational opacity in the FI rating, it presents the optimum setting to try and detect a change in conservatism triggered by a regulatory reform.

According to Jorion et al. (2005) and Henry et al. (2015), rating actions cause large stock price reactions as CRAs enjoy an increased informational advantage (see Section 3.2). However, if the rating is not born out of new information, but rather due to changing behaviour, one would expect to see a diminished reaction to rating signals.

The literature examining the US DFA reforms of the rating industry is limited and is primarily focused on the corporate rating sector (see Section 2.3.5). Opp et al. (2013) develop a theoretical framework that examines the variation in credit rating standards across asset classes over time. They predict that the DFA will result in a systematic *downward shift* in the distribution of ratings from CRAs, caused by the lowering of regulatory advantages for higher ratings.[122] Bolton et al. (2012) argue that the DFA will impact CRAs behaviour by increasing CRAs liability for their ratings, but that it is lacking key reforms to significantly reduce CRAs conflicts of interest. Duan and Van Laere (2012) state that the DFA's attempt to enforce a higher standard of conduct on CRAs has been disappointing.

The most significant study on the impact of the DFA on the rating industry is Dimitrov et al. (2015). They empirically analyse the impact of the DFA on corporate bond ratings (excluding FI ratings from their sample). Using Fitch market share across industries as a proxy for reputational concerns (building on the work of Becker and Milbourn (2011)), they find that following the introduction of the DFA, in industries where CRAs care more about their reputation; rating levels decrease (confirming the prediction of Opp et al. (2013)), the incidence of false warnings increases and the bond and stock price reaction to rating downgrades are diminished, implying less informative corporate ratings. These results support *reputation hypothesis* in the post DFA regulatory period. However, they neglect a number of important

[120] Potentially caused by issuer opacity.
[121] Particularly in crisis periods (Flannery et al., 2013), see Section 2.2.8.2.
[122] In line with the regulatory licence view of ratings (see Section 2.2.9).

points (i) they do not (as Bae et al. (2015) suggest) control for the difference between regulated and non-regulated industries, (ii) control for industry specific effects, (iii) control for the impact of reputational shocks during their target period and (iv) control for the implementation of the EU regulation. These criticisms aside they do present compelling evidence that the DFA has impacted the US corporate rating industry and that the impact has not come in the form that regulators have anticipated. They argue CRAs issue lower, less accurate and less informative ratings following the DFA when their reputational costs are greater.

Behr et al. (2018) examine historic US CRA regulation, and find that the US SEC regulations in 1975, which gave CRAs increased market power by increasing barriers to entry and regulatory reliance on credit ratings, led to increased rating inflation. This is highly relevant as the recent regulation in both the US and the EU have attempted to reduce regulatory reliance on ratings and reduce barriers to entry, thereby reversing the trend from the 1970s. Following the results of Behr et al. (2018), this would suggest that reducing CRA market power could consequently reduce the propensity of rating inflation (see Section 2.2).

Jankowitsch et al. (2016) investigate whether the informational content of ratings varies with different economic environments and analyses the case of the US post DFA period. They show that following the DFA, rating signals lead to significantly stronger market reactions for non-financial bonds and weaker reactions for financial bonds. This implies that the US CRA regulation has an ambiguous effect. Clearly, there is more work needed to break down the impact of the regulation, particularly on financial institution ratings which are often ignored due to the increased complexity of FIs.[123]

To summarize, most US studies have focused on the regulations impact on corporate and structured finance rating markets. The focus on corporates is most likely down to the more complicated nature of FI ratings, however, this does not diminish the need for more literature investigating the impact of the recent regulatory changes on FI rating quality and levels. Due to the increased information opacity in FIs, it is possible that their ratings may be the most susceptible to influence by the regulation. Additionally, there is no study that directly compares the EU and US regulatory reforms and their impact on the ratings market. Considering the importance of the regulatory reforms it is vital that the two regimes are contrasted and evaluated over their relative successes.

[123] As discussed in Chapter 3 and Section 2.3.4 the literature covering the European regulation predominantly focuses on sovereign ratings and corresponding regulatory impacts.

4.3 DATA

FI ratings provide a suitable medium for investigating the research questions, as in the US they were not the primary factor behind many of the regulatory changes. The reforms of the DFA were (as with the earlier EU reforms) primarily driven by problems rating structure financial products in the run up to the 2008 financial crisis. The reforms are however applicable to the FI rating market.

The US dataset consists of 454 rated FIs from across the US during the period 1st January 2005 to 1st June 2016.[124] FI ratings are obtained from Bankscope, CRAs' publications, S&P capital IQ and Compustat databases, while accounting variables are obtained from BankScope. The distribution of FIs across states is displayed in Table 4.1, which shows that of the 454 FIs, 289 are rated by S&P, 276 by Moody's and 363 by Fitch (see Table 4.1). Annual financial variables are used in order to maximise data coverage in the sample and only FIs that are rated and have financial characteristics available during the sample period are included. FIs may enter or exit the sample throughout the sample period to avoid any potential "survivor bias".

As in Chapter 3, a panel dataset is constructed using a monthly frequency (as in Caporale et al., 2012; Chen et al., 2016) and the daily rating data and annual accounting data mapped onto it. The correlation matrix (Figure 4.1) shows no evidence of collinearity among control variables. Table 4.2 presents the descriptions and summary statistics for the variables, which are selected following the literature on the determinants of FI ratings (see Chapter 3 Table A. 3.6).

The distribution of non-interest income to gross revenue (%) for FIs in the sample is shown in Figure 4.2, this ratio indicates what proportion of the FI's business is in more traditional interest taking business such as loans and what comes from alternative business such as fee based activity. The figure shows a normal distribution of FIs centred on a ratio of approximately 0.25, meaning that on average the FIs in the sample get 25% of their revenue from non-interest income, i.e. not from traditional loan making activities. While there is a rough distribution of FIs, a second smaller peak is observed at 0.75, this is likely investment FIs that get the majority of their income from non-interest activities.

[124] As in Chapter 3, the sample of FIs are what BankScope classifies to be "banks" that were active at some point during the sample period.

Credit rating data (notch level, outlook and watch) is mapped to the 52-point comprehensive credit rating (CCR) scale: AAA/Aaa = 52, AA+/Aa1 = 49, AA/Aa2 = 46 …, CCC+/Caa1, CCC/Caa2, CCC-/Caa3 = 4, C/SD/CC/D = 1 Chapter Then, for positive (negative) watch +2 (-2) is added and for positive (negative) outlook +1 (-1) is added (as in Section 3.3 and Table A. 3.1 in Chapter 3).[125] The distribution of ratings in the US sample is shown in Figure 4.3 (and broken down in Table A. 4.1). The figure shows that S&P/Moody's issue slightly higher ratings (peaks at A-/A3) than Fitch's (peaks at BBB) and that the sample is well distributed across rating categories.

The distribution and magnitude of rating upgrades and downgrades in the sample is reported in Table 4.3 and the returns in Table A. 4.3. There are 615 rating downgrades and 459 upgrades during the period. These are composed of 474 greater than 1 notch rating changes and 600 less than 1 notch changes. There are 406 S&P, 265 Moody's and 403 Fitch rating events in the sample. There is a spike in the number of rating downgrades in 2008 and 2009 following the financial crisis.

Control variables are included to reduce the time varying heterogeneity in the FIs and to account for variation in FIs characteristics that could be driving changes in their ratings. Seven control variables are utilized: asset quality, management efficiency, profitability, revenues, leverage, liquidity and size (these are defined and explained in Section 3.3). Many of these are also employed by other studies in the literature to determine FI ratings (Huang and Shen, 2015; Hau et al., 2013; Shen et al., 2012). Table A. 3.2 in Chapter 3 reports the control variables included in the model and the papers that employ them to model FI ratings.

The control variable data is trimmed to remove outliers, with the bottom and top 0.5% is trimmed from ROAA and Equity to total assets, while the top and bottom 1% is trimmed from Cost to income ratio, Loan loss provisions to net interest revenue, Non-interest income to gross revenues and Liquid assets to deposits and short-term funding. Total assets did not require trimming. The resulting summary statistics are displayed in Table 4.2. All variables have reasonable means and vary within the expected ranges.

[125] Eq. (4.1) to (4.3), produced equivalent results (see Table A. 4.5 and Table A. 4.8 in the Appendix) when using the 18-notch rating scale (which excludes outlook and watch signals) as used by Becker and Milbourn (2011) and Dimitrov et al. (2015). See Section 4.5.4.

4.3.1 FALSE WARNINGS

A warning is defined, as in Chapter 3 Section 3.3.1, as a period in which a FI is rated BB+ or below.[126] A false warning is defined as a warning for a FI that does not default in the following 12 months.[127] A FI may receive both true and false, although they must occur in separate time periods, e.g. warning is issued too early.

As in Chapter 3, a limitation of the method is the lack of occurrences of false warnings, in the sample. Of 454 FIs, 125 had warnings issued over the sample period and of these 110 at some point incurred a false warning.[128] Throughout the sample S&P, Moody's and Fitch issue false warnings to 43, 44 and 73 FIs respectively (a more detailed breakdown is show in Table A. 4.2). The incidence of false warnings throughout the sample period is illustrated in Figure 4.4 which shows that the incidence of false warnings increases from 2008 to 2015. The increase appears to be due to the increase in warnings during the period, which arises due to the financial trouble caused by the 2008 financial crisis.

The same process used in Chapter 3 (Section 3.3.1), is applied here to create the sample. All the warnings (ratings falling to or below BB+)[129] are identified in the sample. Information on these FIs is then gathered from Bankscope, Bloomberg, S&P's CapitalIQ and Kerlin et al. (2016),[130] as well as from the CRAs themselves. Actual FI failures are rare in the US, as in Europe, and therefore defining when a FI faces distress can be challenging. Betz et al.'s (2014) method is adopted here, whereby FIs with warnings are examined for potential distress events, which include: (i) default/liquidation, (ii) government intervention/support and (iii) forced merger (See Chapter 3, Section 3.3.1 for more details).

4.3.2 STOCK MARKET DATA

Stock market data for 110 listed FIs and the US indexes (the Dow Jones, NASDAQ and S&P500) are collected for the period 1st January 2005 to 1st June 2016 from DataStream. The summary statistics are shown in Table A. 4.4, where there are 169,375 observations used over the period 1st January 2005 to 1st June 2016 and 486 rating events (including outlook and watch)

[126] There are usually multiple instances for each FI, as a FI may hold a low rating for many months or years.
[127] False warnings are alternatively defined using B+ as the cut-off and a period of 24 months. The results of the robustness tests are consistent (see Section 4.5.4).
[128] This is, however, more than were observed in Chapter 3.
[129] 8 points on the 18-point scale
[130] Some of these FIs also appeared in the paper Ayadi and Thyri (2015), whereby they are double checked.

and 240 (excluding outlook and watch). The abnormal stock returns are then calculated for each day using Eq. (4.6) and a 200-day event window (see Section 4.4.3).

The breakdown between rating announcements by S&P, Moody's and Fitch is shown in Table 4.3, along with the number of rating, outlook and watch positive and negative signals. It should be noted that during the sample there is significantly more negative than positive credit signals issued by all three CRAs. S&P issues the highest number of negative signals during the sample (214), while Moody's issues the lowest (6). S&P issues the highest number of positive signals (169) while Moody's again issues the least (5). Of the negative signals, 58% involved a rating category change, while only 39% of positive signals involved a rating category change (see Table 4.3). Most rating changes are at 1-CCR (outlook), 2-CCR (watch) and 3-CCR (one-notch) points. But there are cases of downgrades by greater than 9-CCR (greater than 3-notch). The clustering of rating events can impact the reaction of the stock prices to rating signals (Williams et al., 2015), so to account for the clustering of rating events, in addition to the whole sample both intendent and clustered events are considered separately as robustness test (see Section 4.5.4 and Table A. 4.12).

4.3.3 FITCH MARKET SHARE

To distinguish between markets with greater and lesser reputational concerns it is necessary to develop a proxy. Fitch market share is a suitable proxy and is inspired by the work of Becker and Milbourn (2011) and Dimitrov et al. (2015). These two studies chose Fitch market share as a proxy for reputational concerns in the US ratings market, as Fitch has a much weaker presence in that market. Becker and Milbourn (2011) argue that the increasing presence of Fitch (which had the lowest market share) causes S&P and Moody's to be increasingly competitive and thus care less about their reputation. S&P and Moody's are then more likely to inflate ratings in industries with higher Fitch market share, which is what both studies found.

This Chapter's sample, the US FI ratings market, includes the presence of S&P, Moody's and Fitch. Fitch has an average market share over the period 2004-2016 of 35.76%. However, the FIs rated by Fitch are substantially smaller than those rated by S&P and Moody's. Fitch FIs have median assets of $15 billion, while S&P and Moody's have median assets of $33 billion and $30 billion respectively (see Table 4.4). It is concluded that the proportion of business is greater for S&P and Moody's than for Fitch.

Fitch market share is calculated by state rather than industry and hence avoids the issue of the difference between regulated and nonregulated industry that Bae et al. (2015) claims is a source of bias in previous studies, as the regulation is applied homogenously and simultaneously across states. This study also avoids the issue of unobservable industry affects by limiting the sample to a single industry. To further strengthen the evidence and to counter the argument highlighted by Bae et al. (2015), that Becker and Milbourn (2011) results may be being driven by industry effects, Eq. (4.1) is performed both with and without controlling for state and year effects. The results (see Table 4.6) show that Fitch market share is a significant factor and that the variation cannot be explained by changes in regional (state level) effects.

Fitch market share is calculated by dividing the number of Fitch issuer ratings (assigned to FIs) in country *j* in year *t* by the total number of FI issuer ratings assigned by the big three CRAs in country *j* in year *t* (the resulting market share is lagged by 1 year in estimated models). Figure 4.5 shows that the average Fitch market share varies sufficiently across all states in the US sample and time periods. Fitch market share in the sample varies from an average of 31.48% in 2005 and rises to 31.41% in 2016. Fitch market share also varies across states from 4.76% in Kansas to 64.10% in South Carolina. It is then necessary to confirm that Fitch market share (FMS) can be used as a proxy for reputational concerns. The inference is that S&P and Moody's assign higher ratings in states with higher Fitch market share (lagged by 1 year). The following ordered logit model[131] is estimated:

$$\mathrm{CR}_{i,j,k,t} = \beta_1 \mathrm{FMS}_{t-1} + \beta_2 \mathrm{BANK}_{i,j,k,t-1} + \beta_3 \mathrm{Moody's}_t + \beta_4 \mathrm{Fitch}_t + \lambda \mathrm{SF} * \mathrm{YF} + \varepsilon_{i,j,k,t} \qquad (4.1)$$

The dependent variable, $\boldsymbol{CR_{i,j,k,t}}$, is the rating of FI *i* in state *j* by CRA *k* at time *t* based on the 52-point CCR scale. $\boldsymbol{FMS_{t-1}}$ is Fitch market share (lagged by 1 year), defined as a dummy variable with a value 1 for FIs in countries within the lower quartile of Fitch market share and zero within the upper three quartiles of Fitch market share.[132]

BANK is a set of FI control variables, including asset quality, efficiency, profitability, revenues, leverage, liquidity and size (see Table 4.2), ***Moody's*** and ***Fitch*** are dummy variables that distinguish between ratings assigned by Moody's, Fitch and S&P (both dummies are zero for ratings assigned by the latter). ***SF * YF*** is a full set of state and year interacted dummy variables. The use of interacting fixed effects is an increasingly common practice (e.g. Jiménez

[131] The results of Eq. (4.1) is robust to using ordered probit estimations (see Panel C of Table A. 4.7).
[132] The results of Eq. (4.1) are also robust to using both 10^{th} and 40^{th} percentiles of Fitch market share in the $\boldsymbol{FMS_{t-1}}$ dummy, and also to using the percentage market share in each country. See Panel A and E of Table A. 4.7.

et al., 2012), as the approach allows for the control of possible omitted variable bias which can result in endogeneity issues (see Section 4.4.1). The interaction term takes account of any variation present across different times and countries, and controls for differences in the macroeconomic conditions of the countries. The results (see Panel D of Table A. 4.5) of Eq. (4.1) are robust to using not interacting fixed effects.

The results of Eq. (4.1) are shown in Table 4.5 and are consistent with the expectation that Moody's and S&P issue lower ratings in states in the lower 25th percentile than the upper 75th percentile. Fitch market share with $\boldsymbol{FMS_{t-1}}$ being negative and significant. The coefficient of FMS is -4.838 implying that the odds that FIs are rated non-investment grade are 126 times greater for FIs located in states in the lower 25th percentile of Fitch market share compared to FIs located the upper 75th.

It is also confirmed that Moody's and S&P issue higher ratings in states with higher Fitch market share.[133] This confirms that Moody's and S&P are less concerned about their reputation and thus more likely to inflate their FI ratings in states with higher Fitch market share.

[133] Tested using the reverse dummy variable, zero in the bottom 25th percentile of Fitch market share and 1 otherwise.

4.4 METHODOLOGY and hypotheses

This Section discusses the methods of examining the impact of the US regulatory reforms on the quality of ratings. Three hypotheses are tested, namely the *disciplining*, *conservatism* and *reputation* hypotheses. The Section composes of three sub-sections. Section 4.4.1 examines rating levels, Section 4.4.2 investigates false warnings, and Section 4.4.3 analyses the informational content of ratings.

Three hypotheses predictions are tested. *Disciplining* hypothesis predicts that the regulation induces improvements in rating quality and hence in the post regulatory period CRAs issue lower (less inflated) ratings, fewer (or no change in) false warnings and more informative rating announcements. *Rating conservatism* predicts that CRAs will lower ratings to avoid increased regulatory scrutiny, fines and liability, there will be a corresponding increase in the frequency of false warnings and a reduction in the informativeness of rating downgrades. *Reputation* hypothesis predicts that in the post regulatory period CRAs are more protective of their reputation and issue lower ratings, an increase in false warnings and less informative rating downgrades in markets where they care more about their reputation. For a summary of the empirical predictions see Section 3.3.4.

4.4.1 RATING LEVELS

One of the primary objectives of the DFA is to eliminate rating inflation.[134] The clearest indication of success would be a decrease in rating levels following the implementation of the regulation. Therefore, this Chapter first examines whether rating levels decreased in the post regulatory period. A decrease in ratings would be consistent with all three hypotheses. *Disciplining hypothesis* predicts that the regulation stimulates improvements in CRAs methodology and rating process (e.g. removal of bias) which leads to a reduction in rating inflation. *Rating conservatism* predicts that CRAs will under rate issuers to avoid the increased regulatory penalties and fines. *Reputation hypothesis* predicts that CRAs lower ratings to protect and rebuild their reputation. To test this, an ordered logit regression model is estimated as follows:

[134] As with the EU regulation, see Section 3.4.1.

$$CR_{i,j,k,t} = \beta_1 Post_t + \beta_2 BANK_{i,j,k,t-1} + \beta_3 Moodys_t + \beta_4 Fitch_t + \lambda SF * YF + \varepsilon_{i,j,k,t} \qquad (4.2)$$

The dependent variable, $\boldsymbol{CR_{i,j,k,t}}$, is the credit rating of FI *i* in state *j* by CRA *k* at time *t* based on a 52-point comprehensive credit rating (CCR) scale, see Section 4.3. ***Post*** is a dummy variable capturing the regulatory change, i.e. it takes the value of one after the new regulation has been introduced and zero before. The DFA was implemented on the 21st July 2010 as this is when the first wave of regulatory reforms was published by the SEC[135] (see Section 2.3.3).[136] ***BANK*** is a set of variables that control for FI specific characteristics (see Table 4.2). ***Moody's*** and ***Fitch*** are dummy variables that distinguish between ratings assigned by Moody's, Fitch and S&P (both dummies are zero in the latter case). ***SF*** and ***YF*** are a full set of interacted state and year dummy variables.

Naturally there is regional variation in economic conditions across both states and over the sample period.[137] During the sample period, there is also a pre-crisis boom, financial crisis and subsequent recovery. Hence, the changing economic conditions must be accounted for, this achieved via the use of interacted state level and year fixed effects (see Jiménez et al. (2012) and Section 3.4.1).[138] The results are robust to using non-interacted state and year dummies (see 4.5.4 and Table A. 4.10).

The *reputation hypothesis* can be distinguished from the other to as it predicts that the effect should be stronger in markets (states) where CRAs care more about their reputation. To examine the variation in reputational effects, the model additionally considers whether the FI is in a state with stronger or weaker reputational concerns, captured using Fitch market share (see Section 4.3.3). In states with a greater presence of the third CRA, the incumbent CRAs will be increasingly competitive (Becker and Milbourn, 2011; Dimitrov et al., 2015) and consequently inflate ratings, the data confirms this relationship (see Section 4.3.3). Conversely, states with a lower Fitch market share are characterised by greater reputational concerns for Moody's and S&P. If the regulation acts to impact reputational concerns, then the effect should

135 The pre-regulatory period in the US is defined as 1st January 2005 (beginning of the sample) to 20th July 2010 and the post regulatory period as 21st July 2010 to 1st June 2016.
136 A second wave of regulatory updates was enacted between November 2014 to June 2015 (see Section 2.3.3), however there is not enough data in the sample to test this.
137 E.g. variation in economic development, the industrialisation level or geographical bias.
138 The use of interacting fixed effects is becoming an increasingly common practice (Klusak et al., 2017; Jiménez et al., 2012; Thompson, 2011), as the approach allows for the control of possible omitted variable bias which can result in endogeneity issues. The identification of macroeconomic conditions comes purely from the interactions. This is achieved in a similar fashion to that employed in Chapter 3, but with the regional variation on a state rather than country level. It is also necessary to drop any macroeconomic variables as they would be collinear with the dummy variables.

be magnified in these states. *Disciplining hypothesis* or *rating conservatism* do not impact reputational concerns and as such the impact of these two should not vary with reputational concerns (see Section 3.3.1). The following ordered logit model is estimated:

$$CR_{i,j,k,t} = \beta_1 Post_t + \beta_2 FMS_{j,t-1} + \beta_3 Post * FMS_{i,j,t-1} + \beta_4 BANK_{i,j,k,t-1} + \beta_5 Moodys_t + \lambda SF * YF + \varepsilon_{i,j,k,t} \quad (4.3)$$

The regression model is the same as Eq. (4.1) except for the additional term ***FMS*** and ***Post*FMS***. The sample is split into two sub groups, the lower quartile of FMS and the upper three quartiles of FMS. The variable $\boldsymbol{FMS_{j,t}}$ is a dummy variable with a value of one if in the first group and zero if in the second. The addition of the interaction ***Post*FMS*** allows for the extraction of the effect due to variations in reputational concerns in the post regulatory period and thus ***Post*** represents the change arising solely from the regulation.

4.4.2 FALSE WARNINGS

This Section tests whether the lower credit ratings in the post regulatory period are the result of justified or unjustified downgrades (i.e. warranted by changing FI creditworthiness). If any change in rating levels is fully justified, there will be no significant increase in false warnings (see Section 4.3.1). If the observed lower ratings are not fully justified, an increase in false warnings would be identified (i.e. unjustified downgrades). The following logit model of false warnings is estimated:

$$FW_{i,j,k,t} = \beta_1 Post_t + \beta_2 BANK_{i,j,k,t-1} + \beta_3 Moodys_t + \beta_4 Fitch_t + \lambda SF * YF + \varepsilon_{i,j,k,t} \quad (4.4)$$

The form is the same as Eq. (4.1) except for the dependent variable, $\boldsymbol{FW_{i,j,k,t}}$, which is a dummy variable with a value of one for a BB+ or lower[139] rated FI *i* in state *j* by CRA *k* at time *t* that doesn't default within one year and zero otherwise (see Section 4.3.1). In the US, as in the EU (see Section 3.3.2), actual FI failures are rare and therefore this Chapter adopts the same definition of FI failures and distress events as used in Chapter 3.

As in Chapter 3, the three hypotheses make different predictions with regards to false warnings. The *disciplining hypothesis* predicts no increase in the number of false warnings, because the

[139] The results of Eq. (4.4) and Eq. (4.5) are robust to using a rating of B+ and below as the cut off point for a warning instead of the original cut off point of BB+ and to changing the length of time to observe financial distress from one year to two years (see Section 4.5.4 and Table A. 4.9).

regulation has stimulated improvements in rating methodology and the subsequent decrease in rating levels is warranted. *Rating conservatism* predicts an increase in the number of false warnings, as greater risk of regulatory intervention causes CRAs to under-rate, thereby inducing an increased incidence of unwarranted downgrades. *Reputation hypothesis* predicts an increase in false warnings as CRAs unjustifiably downgrade ratings to protect their reputation, the effect should be magnified in markets (states) with stronger reputational concerns (see Section 4.3.3). To test for the presence of reputational effects the following model is estimated:

$$FW_{i,j,k,t} = \beta_1 Post_t + \beta_2 FMS_{j,t-1} + \beta_3 Post * FMS_{i,j,t-1} + \beta_4 BANK_{i,j,k,t-1} + \beta_5 Moodys_t + \lambda SF * YF + \varepsilon_{i,j,k,t} \tag{4.5}$$

The interaction term ***Post * FMS*** represents the difference in impact between states with stronger and weaker reputational concerns. A positive and significant interaction term would indicate a stronger effect increase in false warnings in states with greater reputational concerns. ***Post*** captures the change due to the increase in *rating conservatism* caused by the regulation. A positive and significant coefficient would indicate an increase in false warnings due to the regulation.

4.4.3 INFORMATIONAL CONTENT OF RATINGS

This Section examines how the informational content of rating announcements have been affected by the US regulatory changes. The quantity of information contained with rating announcements is used as measure of rating quality and can be gauged by examining the size of the market reaction. This reaction arises as investors and market participants react and digest the new information transmitted to the market by the rating announcement. The market reaction to a rating event on day *t* is measured by the abnormal stock return, calculated using the same technique as in Chapter 3, which widely adopted in the literature (e.g. Correa et al. 2014; Behr and Güttler 2008):

$$Abnormal\ Return = Stock\ Return - \alpha - \beta * Market\ Return \tag{4.6}$$

The FI stock return is calculated over a 2-day period (*t-1*, *t+1*). α and β are the intercept and slope coefficients, respectively, of an OLS regression of FI *i*'s stock returns on the market return estimated using daily data from an event window of 230 days prior to 30 days prior [-230, -30] each rating announcement and a constant.[140]

A OLS model of rating announcements with state and year interacted fixed effects is constructed (rating upgrades and downgrades are considered separately) as follows:

$$AR_{i,j,k,t} = \beta_1 Post_t + \beta_2 Rating\ Event_{i,j,k,t} + \beta_3 Post_t * Rating\ Event_{i,j,k,t} + \beta_4 BANK_{i,j,k,t-1} + \beta_5 Moody's_t + \beta_6 Fitch_t + \lambda SF * YF + \varepsilon_{i,j,k,t} \quad (4.7)$$

Rating Event**$_{it}$* is a dummy variable equal to 1 on a credit rating event date *t* for FI *i* and zero otherwise. ***AR is the abnormal stock return and is calculated as in Eq. (4.6).

As in Chapter 3, the *disciplining hypothesis* states that improved methodologies, diligence and reduced rating inflation will result in improvements in rating quality and rating downgrades and upgrades will become more informative. *Rating conservatism* states that downgrades will become less informative, because CRAs deflate their ratings to protect themselves against increased regulatory intervention. Conversely, rating upgrades may become more informative, as over-rating exposes CRAs to greater potential penalties and liability, which incentivises CRAs to expend greater effort to ensure that each upgrade is warranted. The *reputation hypothesis* makes the same predictions as *rating conservatism* as CRA seek to protect their reputation, but that the effect is magnified in states with greater reputational concerns.

This Chapter also estimates Eq. (4.8), whereby the interaction term ***Post*Rating Event********FMS*** is the additional effect that FI rating events have in states in the bottom quartile of Fitch market share (greater reputational concerns):

$$AR_{i,j,k,t} = \beta_1 Post_t + \beta_2 Rating\ Event_{i,j,k,t} + \beta_3 Post_t * Rating\ Event_{i,j,k,t} + \beta_4 FMS_{i,t-1} + \beta_5 Rating\ Event_{i,j,k,t} * FMS_{i,t-1} + \beta_6 Post_{i,t} * FMS_{i,t-1} + \beta_7 Post_{i,t} * Rating\ Event_{i,j,k,t} * FMS_{i,t-1} + \beta_8 BANK_{i,j,k,t-1} + \beta_9 Moody's_t + \beta_{10} Fitch_t + \lambda CF * YF + \varepsilon_{i,j,k,t} \quad (4.8)$$

A summary of the empirical predictions of each hypothesis can be found in Section 3.4.4.

[140] Stock market data for 110 listed FIs and the US indices is collected from DataStream (see Section 4.3.2).

4.5 EMPIRICAL RESULTS

4.5.1 RATING LEVELS

This Section analyses the DFA's impact on FI ratings levels. To preview the findings, this Section shows that: (i) the regulation has no overall impact on the US FI rating levels, (ii) each CRA has responded differently to the regulation. First, all the CRAs are considered together before considering each CRA separately.

Firstly, Eq. (4.2) is estimated for the entire sample using the 21st July 2010 as the start of the post-regulatory period, with the results reported in Panel A of Table 4.7. The coefficient of the regulatory change ***Post*** is insignificant, indicating that the passage of DFA does not significantly affect the levels of FI credit ratings. The result does not support any of the research hypotheses: *disciplining hypothesis*, *rating conservatism* and *reputation hypothesis*. This contrasts to evidence from the US corporate rating market, where reputational concerns drive a fall in rating levels (see Dimitrov et al., 2015), and the EU FI rating market, where an increase in *rating conservatism* is observed, see Chapter 3.

Then, Eq. (4.2) is estimated using rating data from each of the three CRAs (Moody's, S&P and Fitch) separately (results reported in Panel A of Table 4.7). The results show that each of the three CRAs respond differently to the enactment of the DFA. Moody's FI rating levels are significantly lower in the post-DFA period, the ***Post*** coefficient is -0.089*** (the odds that a FI is rated as non-investment grade by Moody's are 1.09 times[141] greater following the CRA regulatory reforms). S&P FI ratings are not affected by the passage of DFA (***Post*** is insignificant). Fitch FI ratings are significantly higher in the post-DFA period, with the ***Post*** coefficient is 0.128*** (and thus the odds that a FI is rated as non-investment grade by Fitch are 1.14 ($1/e^{0.128}$) times greater following the regulation).

Eq. (4.3) is estimated to take account of differences between states with different reputational concerns, with the results also reported in Panel B of Table 4.7. Rating signals are restricted to those of Moody's and S&P and the estimated model includes the Fitch market share variable. Once again for the sample as a whole, ***Post*** coefficient remains insignificant. The results also imply a lack of evidence in support of the *reputation hypothesis* as the coefficient of the

[141] This can be obtained by $\frac{1}{e^{-0.089}} = e^{0.089} = 1.09$ times greater.

interaction term ***Post * FMS*** is insignificant. Then, Eq. (4.3) is estimated using a rating sample from each CRA (S&P and Moody's) separately.

Moody's FI rating levels are significantly lower following the passage of the DFA (***Post*** is -0.071***, and thus the odds that a FI is rated as non-investment grade by Moody's are 1.07 times greater following the regulation). The coefficient of interaction term ***Post * FMS*** is insignificant, indicating lack of supporting evidence for the *reputation hypothesis*. Therefore, the results suggest either that the disciplining effect of the regulation is leading to improvements in Moody's FI rating quality; by reducing rating inflation and the downgrades are warranted, or that with the increased regulatory stringency and liability, Moody's tend to rate FIs more conservatively.

The results show that S&P FI ratings are not affected by the passage of DFA (insignificant ***Post***). This suggests that the DFA regulation hasn't led to any reforms in the way S&P rate their FIs, perhaps because they have been already compliant with the standards required prior to the passage of the regulation. It also indicates that the increased regulatory stringency and liability have not caused S&P to rate their FIs more conservatively (as was observed in the EU).[142] The results also show no evidence in support for *reputation hypothesis* (***Post * FMS*** is insignificant) in S&P case. This suggests that S&P's concern for their reputation does not change following the passage of DFA.

Fitch reacts in a different and unexpected way, by exhibiting significantly higher ratings following the passage of the regulation. This may suggest a conservative bias in Fitch FI ratings prior to the regulation that has been eliminated with Fitch is spending greater effort to ensure more accurate FI ratings in post-DFA period (i.e. supporting *disciplining hypothesis*). The results indicate that the three CRAs have responded differently to the passage of the regulation of CRAs.

In summary, each of the three CRAs (Moody's, S&P and Fitch) have responded differently to the passage of DFA. To further understand the separate underlying reasons for the changes by each CRA, it is necessary to examine whether the change in rating levels is warranted or has resulted in an increase in false warnings, as well as the information content of credit rating signals on the post-DFA period.

[142] This lack of conservatism may be driven in part by the lack of any fines in the US brought against CRAs as a result of the regulation (at the time of writing).

4.5.2 FALSE WARNINGS

This Section examines whether the change in rating levels is warranted by subsequent outcomes and distinguishes between *disciplining hypothesis* and *rating conservatism*. To preview the findings: (i) no significant change in false warnings in the post-DFA period, for the sample as a whole and for individual CRAS, (ii) there is no evidence of *reputation hypothesis*.

Firstly, Eq. (4.4) is estimated using the entire sample with the results are reported in Panel A of Table 4.8. Following the enactment of the DFA, there is no change, and crucially no increase, in the occurrences of false warnings for the entire sample (***Post*** is insignificant). This result is consistent with expectations as no significant decrease in rating levels was observed for the entire sample in Section 4.5.1. Hence, there should be no unwarranted decrease in rating levels.

The, Eq. (4.4) is estimated using rating data by each CRA separately. The results (see Panel A of Table 4.8) are consistent in that there is no change in false warnings by each CRA in post-DFA period. This result is particularly relevant to Moody's where a significant decrease in Moody's FI rating levels was observed in post-DFA period. The lack of an increase in false warnings for Moody's supports the rejection of the *rating conservatism* hypothesis in explaining the fall in Moody's rating levels in post-DFA period. This implies that[143] *disciplining hypothesis* is explaining the fall in Moody's rating levels and resulting in a warranted decrease in ratings (hence no increase in false warnings). Further, the results of Eq. (4.4) confirm the supposition that S&P is relatively unaffected by the regulatory reform and suggest that they are already complying to the required level prior to the its introduction. Fitch also exhibits no increase in false warnings, which is expected considering their FI rating levels have risen following the passage of the regulation.[144]

Then, the sample is restricted to rating by Moody's and S&P and Eq. (4.5) is estimated. The results (see Panel B of Table 4.8) for the whole sample and for Moody's and S&P separately reveal no evidence in support of *reputation hypothesis* (insignificant ***Post * FMS***). For each CRA, the coefficient of ***Post*** is also insignificant indicating, in line with the results of Eq. (4.4), that the regulation has no impact on the incidence of false warnings.

[143] Due to the lack of evidence to support *rating conservatism* and *reputation hypothesis*.
[144] Higher ratings will naturally not cause an increase in unjustified downgrades, as rating levels are not falling.

In short, there is no evidence supporting *rating conservatism* and *reputation hypotheses*[145] in the US FI rating market in the post-DFA period when examining both rating levels and false warnings. The results additionally indicate that there is no uniform effect over the whole rating market, but rather each CRA reacts to the DFA in a different manner. These results are in contrast to the US corporate rating market where there is an decrease in rating levels and an increase in false warnings that is magnified in industries with stronger reputational concerns, indicating that *reputation hypothesis* is driving changes (see Dimitrov et al., 2015).[146] They also contrast the EU FI rating market, where there is a fall in rating levels, a corresponding increase in false warnings and no variation in impact with reputational concerns, indicating that increased *rating conservatism* is driving the changes (see Section 3.6).

4.5.3 INFORMATIONAL CONTENT OF RATINGS

This Section compares stock market reactions to FI rating changes before and after the enactment of the DFA.[147] Two approaches are used to examine the change in stock market reaction to (informational content of) rating changes. Firstly, an event study considering just the dates with rating changes and secondly, an OLS model considering all dates in the sample (Eq. (4.7) and (4.8), see Section 4.4.3). To preview the findings: (i) a reduction in rating downgrade informativeness is observed in the post-regulatory period and (ii) rating upgrades have insignificant impact on share prices in both pre- and post-regulatory periods.

The event study results, reported in Table 4.9, show that prior to the July 2010 rating downgrade announcements caused a significant stock price reduction (-3.555%***). After July 2010, there is no significant response to rating downgrades. A t-test confirms a significant decrease (-2.587*) in the reaction to downgrades in the whole sample in the post-regulatory period, indicating that rating downgrades are less informative in the post-regulatory period. When announcements for the three CRAs are considered separately in the event study, the result is consistent across CRAs (see Table 4.9). Moody's, S&P and Fitch issue downgrades that cause a significant stock market reaction (-2.247%*, -4.878%*** and -3.391%**

[145] The lack of any variation, in both rating level and false warning, with reputational concerns indicating that *reputation hypothesis* is not supported in the sample.
[146] Dimitrov et al. (2015) find that the impact of the regulation (decrease in rating levels, increase in false warnings) was stronger in markets with greater reputational concerns.
[147] The focus is only on rating signals based on 18-notch rating scale (i.e. excluding outlook/watch actions).

respectively) prior to the DFA and only S&P's are significant (-1.040%*) in the post regulatory period.

The results of Eq. (4.7) produce equivalent inferences. They show that prior to the enactment of the DFA, rating downgrades resulted in a significant stock price reduction of -3.982%*** (see Table 4.9). After the regulatory reforms of CRA, this reaction is no longer significant (-3.982***+2.958*** = -1.024%),[148] with rating downgrades no longer eliciting such a strong reaction. The same results are observed when Eq. (4.7) is estimated for each CRA separately, with all three CRAs issuing downgrades that elicit a significant stock market reaction in the pre-regulatory period and insignificant reaction in the post-regulatory period i.e. a reduction in rating downgrade informational content (see Table 4.10).

The impact of the passage of the DFA on stock market reactions to rating upgrades is also examined. The results from the event study, see Table 4.9, show that the regulation has no impact on the informational content of rating upgrades, as both prior and post the regulatory change the reactions are insignificant. The result is also consistent when rating upgrades from each CRA are considered separately.

The results (see Table 4.10) of Eq. (4.7) provide an equivalent inference and the stock market reactions to rating upgrades are not significant in both pre- and post-DFA periods. When Eq. (4.7) is estimated separately for each individual CRA (see Table 4.10) the results are consistent. Only S&P issues informative upgrades prior to July 2010. Following the regulatory reforms, all three CRAs issue uninformative upgrades, which is counter to *rating conservatism* and *reputation hypotheses*. Rating upgrades are, however, more likely to elicit a limited market reaction (Henry et al., 2015; Milidonis, 2013) as issuers tend to leak them.

Lastly, the impact of reputational concerns is also considered. The results (see Table A. 4.16) of Eq. (4.8) show no significant difference in stock market reaction to FI rating downgrades between states with greater and lesser reputational concerns following the passage of the regulation. This indicates that reputational effects are not driving the decrease in the informational content of rating downgrades. These results support the overall finding of lack of evidence for the *reputation hypothesis* in the US FI rating context. This is consistent with the EU FI rating market, while contrasts with the US corporate rating market which

[148] ***Rating Downgrade*** is the market reaction to a rating downgrade prior to the regulation. The market reaction to a rating downgrade following the regulation is given by ***Rating Downgrade*** + ***Post * Rating Downgrade***. Where ***Post*** * ***Rating Downgrade*** is the change in the market reaction after relative to before the passage of the regulation. The coefficient of ***Post * Rating Downgrade*** is positive, implying a significant reduction in the market reaction and therefore informational content of rating downgrades.

demonstrates strong evidence of reputational effects, with downgrades in industries with stronger reputational concerns exhibiting a stronger stock market reaction (Dimitrov et al., 2015).

4.5.4 ROBUSTNESS TESTS

The regulation that targeted CRAs has been rolled out incrementally. Following the enactment of the DFA, the EU implemented key reforms, principally the establishment of ESMA in July 2011. To identify whether the EU regulation in some way drives the changes in the US FI rating market, Eq. (4.2) to Eq. (4.5) are estimated with the inclusion of EU regulatory dummy variable, that takes the value of one after 1st July 2011 and zero otherwise. The results (see Table 4.11) are robust to the inclusion of the DFA. When the three CRAs are considered together rating levels still exhibit no significant change. When they are considered separately, Moody's ratings are lower, S&P ratings are not affected, and Fitch ratings are higher in post-DFA period. False warnings show no change for the sample together or for each CRA separately. The EU regulation may be affecting US FI ratings slightly, but it is not the driving force behind the changes for the three CRAs.

As in Chapter 3, Dilly and Mählmann (2016)'s argument that rating quality is counter cyclical, and ratings quality should be higher in an economic downturn, is considered. In the US it would be expected that during the sample period (economic downturn and the 2008 financial crisis) that ratings quality should increase. This would then predict a reduction in false warnings and an increase in the informational content of ratings announcements. The results are, however, that there is no decrease in false warnings and a reduction in the informational content of rating downgrades and upgrades. The hypothesis that the results are driven by cyclical effects can hence be rejected as they would predict different results.[149]

When examining the information content of rating announcements using an event study, it is important to consider the clustering of rating announcements (Williams et al., 2015; Hill and Faff, 2010). An independent rating event is defined as one where no other rating event occurs for the FI within 21 trading days (-10, +11), otherwise the event is a clustered event. There are

---

[149] In the US a bail-in type regulation, called the Orderly Liquidation Authority (OLA), was instigated as part of the July 2010 DFA. As it was brought into effect at the same time as the other reforms, it is not possible to unpick its potential effect (unlike in the EU).

2,695 separate rating events in the sample, of which 2,023 are independent events and 672 are clustered. The results (see Table A. 4.12 and Table A. 4.13) are consistent and while both independent and clustered rating downgrades cause significant decreases in stock prices prior to the regulation, they both have insignificant impact on stock market following the passage of the regulation. Both independent and clustered stock market upgrades are insignificant both pre and post-DFA periods.

Lastly, as explained in Sections 4.4.1 and 4.4.2, the results of Eq. (4.2) to Eq. (4.5) are consistent when they are estimated using Probit or OLS model (see Table A. 4.6 and Table A. 4.7). As stated in Section 4.4.2, the results for Eq. (4.4) and Eq. (4.5) are robust to alternative definitions of false warnings (see Table A. 4.9).[150] As stated in Section 4.4.1, the results to Eq. (4.2) and Eq. (4.3) are robust to the use of the 18-notch rating scale (see Table A. 4.8), which excludes outlook and watch signals. As stated in Section 4.4.1, the results from Eq. (4.2) to Eq. (4.8) are robust to using to using country and year fixed effects separately (see Table A. 4.10, Table A. 4.11 and Table A. 4.15).

[150] Using B+ as the cut off and a period of 24 months.

4.6 THE IMPACT OF EU VS US REGULATORY REFORMS OF CRAS

The EU and US regulatory reforms of the FI rating sector (examined in Chapters 3 and 4 respectively) have results in significantly different outcomes. Principally, that the EU has seen a consistent impact across all CRAs, linked to an increase in *rating conservatism*, and the US exhibits varying reactions across CRAs.

This suggests that effective enforcement of the regulation is as, if not more, significant than the regulation itself. The ESMA in the EU has issued more fines for CRAs than the US SEC (see Section 3.1). Also, the instigation of a civil liability regime has resulted in a consistent decrease in rating levels and an increase in false warnings across CRAs in the EU. This indicates that the lower rating levels are not warranted by EU FI characteristics as they are not accompanied by an increase in default rates, as would be suggested. The key reason for an unjustified decrease in ratings is increasingly conservative rating behaviour in the EU. There is no variation in frequency of false warnings issued for US FIs by any CRA and only Moody's FI rating levels are significantly lower in the post-DFA period.

The only common effect between the EU and US is a reduction in stock market reactions to FI rating downgrades. In the EU this is driven by two factors. Firstly, the increasingly conservative ratings mean that rating downgrades are of lower quality as they are not warranted. Secondly, ESMA has been seeking to mitigate the mechanistic market reliance on rating downgrades. The subsequent increase in stock market reactions to rating upgrades in the EU is consistent with increasingly conservative rating behaviour as CRAs expend more effort to ensure they are warranted and will thereby typically become more informative. In the US, however, there is no evidence for *rating conservatism*. Hence, it would appear that the market is paying less attention to CRA rating downgrades and upgrades of FIs in the US.

The results of both the EU and US FI rating sectors contrast with evidence from the US corporate rating sector, where evidence (see Dimitrov et al., 2015) indicates that it is increased reputational concerns in post-DFA that are driving changes in CRA corporate rating behaviour. The US corporate rating market has showed a clear variation in the effect of the passage of the DFA between industries with stronger and lesser reputational concerns.

The difference in impact observed in the three separate rating sectors (EU FIs, US FIs and US corporate) highlights the importance of investigating the impact of regulation on various rating sectors separately, as regulation that sets out with similar aims, can have widely varying effects dependent upon its implementation and market. Regulators should then consider tailoring regulation to the specific rating sector and ensuring that it is effectively enforced.

The Table below summarise whether the findings of Chapters 3 and 4 provide evidence supporting the research hypotheses.

The Impact of EU vs US CRA Regulatory Reform on FI Rating Sector

Hypothesis	EU	US
Disciplining	Evidence of reduced mechanistic market reactions to negative rating announcements.	While there is no evidence of a market wide impact on ratings, each CRA have reacted to the regulation in a different manner. Moody's FI ratings are significantly lower and are warranted, consistent with the reforms has improved FI rating quality of Moody's. Fitch FI rating levels are significantly higher in the post-DFA period, which may suggest a removal of a negative bias in the pre-regulatory period.
Rating conservatism	Evidence of an increase in unwarranted downgrades, indicative of the strengthening of a conservative rating bias. Correspondingly, negative rating announcements are less informative following the passage of the regulation. Positive rating announcements are more informative, consistent with CRAs expending greater effort to ensure they are warranted.	No evidence of increased conservatism.
Reputation	No evidence of a change in reputational concerns in the post regulatory period.	No evidence of a change in reputational concerns in the post regulatory period.

4.7 CONCLUSION

This Chapter investigates whether the US regulatory reforms of the FI rating industry in response to the 2008 financial crisis have been successful. A sample of 454 financial institutions from across the US rated by S&P, Moody's and Fitch during January 2005 to June 2016 is employed. To better understand the effect of the US CRA regulation, the Chapter examines the impact on rating levels, the incidence of false warnings and the responsiveness of stock markets to credit rating signals (rating informativeness). The key regulatory date considered is the enactment of the DFA on the 21st July 2010.

Three hypotheses on the impact of the regulatory change on credit ratings are tested, namely the *disciplining*, *conservatism* and *reputation* hypotheses. The *disciplining hypothesis* proposes that the regulation succeeds in the objective of increasing rating quality, on the grounds that increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring. The *rating conservatism* hypothesis states that CRAs are exposed to more severe scrutiny and penalties by over-rating (being less conservative), rather than by under-rating (being more conservative). As a result, increased regulatory stringency, fines and liability, increase the penalties for over ratings and cause a shift to more conservative rating behaviour. The *reputation hypothesis* implies that CRAs may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FIs' financial characteristics, in order to protect and rebuild their reputation. The effect strengthens with increased reputational concerns.

The Chapter reveals markedly different results to the EU FI rating industry following the EU regulation of CRAs. There is no evidence to support the *reputation hypothesis* for any CRAs, as no CRA exhibits changes in reputational effects following the passage of the regulation. Specifically, the passage of the DFA has no overall significant effect on the US FI rating industry, reporting no significant impact on rating levels or false warnings. While evidence from rating levels and false warnings indicate that the DFA has had little impact on FI ratings, there is evidence of reduced stock market reaction for FI credit rating signals. This could be due to changing market perceptions, as markets place less emphasis on credit ratings due to evidence that they were incorrect/biased in the past (e.g. in the 2008 financial crisis).

However, each CRA (Moody's, S&P and Fitch) has responded differently in the post-DFA period. While no CRA shows evidence of *reputation hypothesis* or increased *rating conservatism* (see Section 4.5), there is evidence that the regulation has stimulated a change in rating behaviour (*disciplining hypothesis*). Moody's reacts to the passage of the regulation by lowering their FI rating levels, notably there is no accompanying change in false warnings. The implies that the subsequent fall in FI ratings is warranted and that it is not caused by increasing conservative rating practices. Rather, the evidence supports *disciplining hypothesis*, with regulatory reforms has led Moody's to invest in improvements to their methodologies, due diligence and performance monitoring, which is resulting in a justified decrease in rating levels. Moody's is generally regarded as more reputationally concerned, as seen by investors in the US (Livingston et al., 2010). The results show that the lower Moody's FI ratings are warranted, as it is not accompanied by an increase in false warnings. While all three CRAs experience a decrease in stock market reactions to rating downgrades, Moody's downgrades trigger the smallest decrease in the informational content of the three CRAs. This suggests that while the market is paying less attention to CRA downgrades, Moody's is the one they are trusting the most (i.e. it has the smallest decrease in market reaction).[151] Moody's upgrades are insignificant following the passage of the DFA, which again is consistent with investors relying less on credit ratings.[152]

S&P seems relatively unaffected by the passage of DFA, with no changes in their FI rating levels or the incidence of false warnings in the post regulatory period. This could be because S&P was already compliant with the new regulatory standards prior to the introduction of the regulation. Hence, *disciplining hypothesis* implies that it would not cause further changes. As discussed in Section 4.5.1, the lack of effective enforcement of the regulation (evidenced by a lack of fines and regulatory intervention under the new regime) has meant that no increase in *rating conservatism* has been observed. A significant reduction in the market reaction to rating downgrades and upgrades is observed. It may be that the market is reacting less to rating downgrades, as the recent regulation highlights problems within the rating industry and consequently the market may interpret subsequent rating downgrades as the product of a correction (to reduce rating inflation).

[151] Consistent with them being held in higher regard by investors (Livingston et al., 2010).
[152] Rating upgrades typically stimulate small or negligible market reactions compared to rating downgrades (Alsakka et al., 2015).

Fitch reacts to the passage of the regulation in a different way, with higher FI ratings reported in post-DFA period and no significant change in false warnings. This is potentially indicative of the removal of a conservative rating bias that was present in the pre-regulatory period and could signal an increase in Fitch rating quality. Similar to Moody's and S&P, Fitch rating downgrades are less informative in post-DFA period. There is also no significant change in stock market reactions to Fitch rating upgrades, which are insignificant in both pre- and post DFA periods.

In addition to the lack of evidence for *reputation hypothesis*, the results do not provide evidence in support of an increase in *rating conservatism*. Increased conservatism is caused by CRAs fearing regulatory fines, penalties and intervention, but no fines were issued by the SEC for activity related to the FI rating market.[153] This lack of action implies one of two things, either CRAs have been very well behaved and do not warrant such action (which has not been the case in the EU) or the SEC has been ineffective at enforcing the regulation. An additional factor to consider when comparing this result to the EU FI rating market, is that the US regulatory update is an expansion to a pre-existing regulatory regime, rather than the creation of an entirely new regime.[154] As such, one would expect a smaller shift in rating behaviour. The results are robust to the inclusion of the EU regulation, reputational shocks and to alternative definitions of false warnings and of the rating scale (see Section 4.5.4).

The results contrast with evidence from both the US corporate bond ratings market where it appears that reputational effects have driven changes in CRA behaviour subsequent to the DFA (see Section 2.3.5) and to the EU FI rating market where evidence indicates that it is increased *rating conservatism* that is driving the CRAs rating practices (see Section 3.5). Previous studies Becker and Milbourn (2011) and Dimitrov et al. (2015) propose that incumbent CRAs have greater reputational concerns (are less competitive) in markets with the presence of a third CRA with a smaller market share (markets with less competition). While this relationship is confirmed, that incumbent CRAs issue higher ratings in more competitive markets, the results indicate that the passage of DFA does not influence this relationship in the US FI rating sector (contrary to the US corporate rating market where the passage of the DFA heighted reputational

[153] There is one case against S&P on the 21st January 2015 for activities in the commercial mortgage backed securities market, where S&P has a low market share. They are being fined $58m for their role, approximately 1% of their revenue in 2013 ($4.9 billion).
There was a court case against S&P that was settled in 2013, but this was for a breach under the old rules and for the activities during the 2008 financial crisis rather than for a breach under the new regulation.
[154] Prior to the recent regulatory reforms, there was no legislation directly addressing CRAs operating in the EU (Alsakka et al., 2015) and they acted using voluntary self-regulation following the IOSCO code (see Section 2.3.1).

concerns). Counter to evidence from the EU FI and US corporate rating markets, there is no evidence of increased false warnings in post DFA-period for US FI ratings sector. These results confirm no evidence supporting *rating conservatism* and *reputation hypotheses* in the US FI rating market.

The Chapter contributes by furthering the understanding of the US reforms of the FI rating sector. Principally, the results call into question whether the DFA has managed to reform the US FI rating sector and eliminate rating inflation. The only CRA that responded to the regulation by lowering its FI ratings is Moody's. However, the problem of rating inflation was widespread during the financial crisis, and not just limited to Moody's. The success of the regulation is therefore questionable if it has not managed to eliminate rating inflation, and lower FI rating levels for S&P and Fitch. It appears the market is also questioning the quality of FI ratings, with a significant reduction in stock market responses to FI rating signals in the US.

This relative ineffectiveness of the US reforms suggest that US regulators should consider trying more stringent regulatory oversight of the FI rating market and stronger penalties to promote a reduction in rating inflation. This may result in a conservative bias as in the EU but considering the impact of inflated ratings in the 2008 financial crisis, a conservative bias may be preferable to an over estimation of FI stability. Since credit ratings are an important source of information for market participants, regulators should reflect on the need to improve rating quality and promote more informative rating announcements. Hence, regulators should also consider strengthening the methodological reforms, increased disclosure and transparency and promoting increased civil liability, in an effort to encourage CRAs to invest in improving rating quality.

TABLES

Table 4.1: Distribution of FIs in the sample

State	Total	S&P	Moody's	Fitch
Alabama	12	9	9	11
Alaska	1	0	0	1
Arizona	3	1	1	2
California	45	33	33	31
Colorado	1	0	0	1
Connecticut	9	9	7	6
Delaware	15	11	11	13
District of Columbia	3	2	3	3
Florida	16	2	3	14
Georgia	19	7	6	18
Guam	1	0	0	1
Hawaii	7	5	4	6
Illinois	21	13	13	17
Indiana	6	4	5	5
Iowa	3	3	2	2
Kansas	4	2	4	1
Kentucky	1	0	1	1
Louisiana	3	3	3	1
Maine	2	1	2	2
Maryland	11	5	3	9
Massachusetts	13	8	8	13
Michigan	10	7	9	8
Minnesota	14	6	4	13
Mississippi	5	5	5	3
Missouri	7	6	5	5
Montana	2	0	1	2
Nebraska	5	3	2	3
Nevada	5	3	4	4
New Hampshire	2	2	2	1
New Jersey	9	6	4	4
New Mexico	1	0	0	1
New York	56	38	39	46
North Carolina	8	7	7	7
North Dakota	2	1	1	2
Ohio	16	14	15	14
Oklahoma	2	2	2	2
Oregon	2	0	0	2
Pennsylvania	22	11	14	17
Puerto Rico	12	8	5	10
Rhode Island	6	6	5	4
South Carolina	5	4	2	5
South Dakota	4	4	4	4
Tennessee	6	4	4	4
Texas	19	8	15	11
Utah	8	7	7	7
Vermont	2	2	2	2
Virginia	12	8	10	10
Washington	9	2	2	8
West Virginia	1	0	1	0
Wisconsin	7	6	6	5
Total	455	288	295	362

The number of FIs in each state, rated by each CRA present in the sample.

Table 4.2: Control variables description and summary statistics

Section	Variable	Explanation	Measure	Anticipated relation to CCR	Observations	Mean	Std.	Min	Max
Main factors	*Post*	Post regulatory change, dummy variable of one for observations after the regulatory change, zero otherwise.	Regulatory change	-					
	FMS	Fitch market share	Reputational concerns	+/-					
Rating variables	*Moody*	Moody's rating dummy variable	Rating by Moody	+/-					
	Fitch	Fitch rating dummy variable	Rating by Fitch	+/-					
Bank specific variables (*BANK*)	*LLPNIR*	Ratio of loan-loss provisions to net interest revenues	Asset Quality	+	80,268	16.73	24.16	-11.68	144.71
	CIR	Ratio of cost to income	Efficiency	-	80,268	60.80	15.83	10.55	135.07
	ROAA	Return on average assets	Profitability	+	80,268	1.01	1.08	-5.66	6.92
	NIIGR	Non-interest income over gross revenue	Revenues	+	80,268	34.88	21.37	-76.60	98.80
	ETA	Ratio of equity total assets	Leverage	+	80,268	11.26	5.33	0.92	68.63
	LAtoCSTF	Ratio of liquid assets to customer and short term funding	Liquidity	+	80,268	14.65	19.09	1.38	153.72
	Ln(TA)	The natural logarithms of total assets (€)	Size	+	80,268	16.98	1.81	11.10	21.67
Dummy variables	*RF*	Dummy variable for each state	Geographic variation						
	YF	Dummy variable for each year	Variation over time						

Details the variables used in the regression model of rating levels. It must be noted that if the Moody's and Fitch dummy variables are zero then it's an S&P rating. The sample consists of European rated FIs with rating announcements during the period January 2006 to June 2016 in the 27 EU states included.

Table 4.3: Rating announcement

	CCR (outlook and watch)	
	Downgrades	Upgrades
Sample	#Obs	#Obs
S&P	221	185
Moody's	166	99
Fitch	228	175

	Number of events	
CCR point change	Downgrades	Upgrades
1	176	169
2	114	141
3	165	88
4	52	26
5	13	5
6	44	18
7	10	2
8	6	2
9	9	4
10 or more	26	4

The occurrences of rating upgrades and downgrades throughout the sample. This table separates the rating events by CRA and by type and lists the number of rating by magnitude.

Table 4.4: Size of FIs rated by Fitch, S&P and Moody's

	S&P	Moody's	Fitch
Average	132,440,945,522	139,613,999,884	114,082,450,682
Standard Deviation	326,396,108,182	359,120,499,312	339,424,598,440
Median	32,877,101,000	29,793,800,000	15,274,648,000
Max	2,748,579,000,000	3,270,108,000,000	3,270,108,000,000
Min	3,500,000	1,214,000	1,214,000
95%	664,140,450,000	762,948,200,000	539,406,000,000
90%	248,989,766,000	266,685,828,000	185,098,790,000
75%	90,599,497,500	90,142,449,000	65,214,444,000
25%	12,178,600,500	10,359,193,000	4,949,345,500
10%	4,536,532,600	4,070,425,000	880,200,000
5%	1,693,360,100	1,861,459,800	469,123,500

Sizes of FIs rated by S&P, Moody's and Fitch in the US during 2004-2016.

Table 4.5: Fitch market share impact – Principle regression

Variable	Moody's and S&P		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share dummy (t-1)	-4.838***	-4.75	-5.025***	-3.94	-4.452***	-3.86
Moody's	0.913***	8.17				
ROAA	-0.247	-1.17	-0.198	-0.69	-0.299	-1.57
CIR	-0.039***	-3.26	-0.045***	-3.06	-0.036***	-2.84
LLPNIR	-0.031***	-3.68	-0.029***	-2.93	-0.038***	-4.14
Ln(TA)	0.563***	4.62	0.476***	3.29	0.654***	4.42
NIIGR	0.007	0.59	0.007	0.50	0.007	0.60
ETA	0.033	0.97	0.028	0.72	0.037	0.97
LAtoCSTF	0.019**	2.00	0.021*	1.74	0.022**	2.19
State * Year FE	Yes		Yes		Yes	
# Observations	37,259		17,173		20,086	
Pseudo R^2	12.40%		14.90%		11.60%	

Ordered logit model of Eq. (4.1). Results of investigating the relationship between Fitch market share (dummy, 1 in lower 25%, 0 in top 75%, lagged by 1 year) on a state basis and the dependent variable is the FI credit rating (52 point CCR scale) in the US sample during the period 2005 to 2016. Standard errors are clustered by FI and ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table 4.6: Fitch market share impact – Robustness checks

Panel A. Principle regressions

Variable	OLS (1)	OLS (2)	OLS (3)	Ordered Probit (4)
Fitch market share percentage (t-1)	6.288***	11.540***	10.264***	1.535***
	(0.000)	(0.006)	(0.00)	(0.008)
Year dummies	No	Yes	Yes	Yes
State dummies	No	Yes	No	Yes
Firm dummies	No	No	Yes	No
Firm Controls	No	No	Yes	No
# Observations	37,259	37,259	37,259	37,259
Pseudo R^2	2.30%	31.70%	83.10%	5.80%

Panel B. Controlling for both state-fixed effects and firm characteristics

Variable	OLS (1)	Ordered Probit (2)
Fitch market share percentage (t-1)	10.463***	1.557***
	(0.014)	(0.015)
Year dummies	Yes	Yes
State dummies	Yes	Yes
Firm Controls	Yes	Yes
# Observations	37,259	37,259
Pseudo R^2	45.00%	9.40%

*Consistent with Bae et al. (2015), this table shows the results of Eq. (4.1) with a combination of state and year dummies and firm controls. Results of investigating the relationship between Fitch market share (percent) on a state basis and the dependent variable is the FI credit rating (52 point CCR scale) in the US sample during the period 2005 to 2016. Panel A performs the same model as employed in Table 4 in Becker and Milbourn (2011). P-values are shown in brackets and based on standard errors that are heteroskedasticity-consistent. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table 4.7: Rating levels

Panel A: Eq. (4.2)

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.015	-0.62	-0.089***	-3.86	0.032	0.35	0.128***	4.21
Moody's	0.895***	8.71						
Fitch	0.169*	1.73						
ROAA	-0.227	-1.43	-0.198	-0.69	-0.304	-1.57	-0.167	-1.19
CIR	-0.042***	-4.21	-0.045***	-3.06	-0.036***	-2.82	-0.038***	-4.28
LLPNIR	-0.026***	-3.93	-0.029***	-2.93	-0.038***	-4.18	-0.023***	-4.03
Ln(TA)	0.555***	7.84	0.476***	3.29	0.663***	4.44	0.563***	8.78
NIIGR	0.017*	1.88	0.007	0.50	0.006	0.55	0.020***	2.89
ETA	0.045**	2.04	0.028	0.72	0.037	0.98	0.060***	3.08
LAtoCSTF	0.021***	2.86	0.021*	1.74	0.022**	2.21	0.020***	3.08
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	65,495		17,173		20,086		28,236	
Pseudo R^2	11.72%		14.93%		11.67%		12.68%	

Panel B: Eq. (4.3)

	Full Sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.033	-1.30	-0.071***	-3.33	-0.005	-0.06
Fitch market share	-4.838***	-4.75	-5.025***	-3.94	-4.452***	-3.86
Post × Fitch market share	-0.010	-0.12	-0.082	-1.15	0.140	0.52
Moody's	0.913***	8.17				
ROAA	-0.247	-1.17	-0.198	-0.69	-0.299	-1.57
CIR	-0.039***	-3.26	-0.045***	-3.06	-0.036***	-2.84
LLPNIR	-0.031***	-3.68	-0.029***	-2.93	-0.038***	-4.14
Ln(TA)	0.563***	4.62	0.476***	3.29	0.654***	4.42
NIIGR	0.007	0.59	0.007	0.5	0.007	0.6
ETA	0.033	0.97	0.028	0.72	0.037	0.97
LAtoCSTF	0.019**	2.00	0.021*	1.74	0.022**	2.19
State * Year FE	Yes		Yes		Yes	
# Observations	37,259		17,173		20,086	
Pseudo R^2	12.42%		14.93%		11.65%	

The table presents the results of the ordered logit regressions for the sample of US FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch in Eq. (4.2), and by Moody's and S&P in Eq. (4.3). The dependent variable is $\boldsymbol{CR_{i,j,k,t}}$*: the credit rating level of FI i in country j by CRA k at time t based on a 52-point CCR rating scale.* ***Post*** *is a dummy variable that takes the value of 1 after 21st July 2010 and zero otherwise.* ***FMS*** *is a dummy variable that takes the value of 1 in countries in the bottom quartile of Fitch market share and zero in the top three quartiles.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions, see Table 4.2. Standard errors are clustered by FI and a full set of* ***state*year dummies*** *are included. ***, **, * represent significance at the 1%, 5% and 10% levels respectively.*

Table 4.8: False warnings

Panel A: Eq. (4.4)

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.112	-1.07	-0.125	-0.85	0.007	0.13	-0.093	-0.44
Moody's	0.117	0.58						
Fitch	0.302	1.42						
ROAA	0.197	1.21	0.136	0.46	0.204	0.89	0.182	0.98
CIR	0.030***	2.89	0.009	0.46	0.022	1.32	0.049***	4.13
LLPNIR	0.032***	5.25	0.037***	3.77	0.045***	3.81	0.023***	3.10
Ln(TA)	-0.515***	-4.64	-0.332	-1.29	-0.695***	-3.37	-0.639***	-5.05
NIIGR	-0.009	-0.92	-0.002	-0.11	-0.001	-0.09	-0.015	-1.48
ETA	-0.085**	-2.16	-0.108*	-1.93	-0.158***	-2.97	-0.077	-1.50
LAtoCSTF	0.007	0.70	0.008	0.67	0.029**	2.28	0.005	0.37
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	34,893		5,163		5,631		12,135	
Pseudo R^2	28.16%		19.90%		25.46%		31.80%	

Panel B: Eq. (4.5)

	Full Sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.064	-0.72	-0.318	-0.87	0.019	0.34
Fitch market share	-3.809**	-2.18	-3.879**	-2.02	-3.105**	-2.08
Post × Fitch market share	0.037	0.35	0.318	0.87	-0.050	-0.32
Moody's	0.108	0.50				
ROAA	0.152	0.67	0.136	0.46	0.203	0.89
CIR	0.014	0.92	0.009	0.46	0.022	1.32
LLPNIR	0.039***	4.66	0.037***	3.78	0.045***	3.81
Ln(TA)	-0.514***	-2.60	-0.331	-1.29	-0.695***	-3.37
NIIGR	-0.003	-0.21	-0.002	-0.11	-0.001	-0.09
ETA	-0.116***	-2.70	-0.108*	-1.93	-0.158***	-2.97
LA to CSTF	0.020*	1.78	0.008	0.66	0.029**	2.27
State * Year FE	Yes		Yes		Yes	
# Observations	13,448		5,163		5,631	
Pseudo R^2	24.12%		19.91%		25.46%	

The table presents the results of logit regressions for the sample of rated US FIs during the period January 2006 to June 2016 rated by S&P, Moody's and Fitch in Eq. (4.4), and by Moody's and S&P in Eq. (4.5). The dependent variable $\boldsymbol{FW_{i,j,k,t}}$*, a dummy representing false warnings, takes the value of 1 if an FI with a rating of BB+ or below does not default after one year and zero otherwise.* ***Post*** *is a dummy variable that takes the value of 1 after 21st July 2010 and zero otherwise.* ***FMS*** *is a dummy variable that takes the value of 1 in countries in the bottom quartile of S&P market share and zero in the top three quartiles.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions see Table 4.2. Standard errors are clustered by FI and a full set of* ***state*year dummies*** *are included. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table 4.9: Informational content – Event study

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic
Credit rating downgrades	Full Sample	#Obs	247	105		
		Mean return (%)	-3.555***	-0.968	-2.587*	-1.88
	S&P	#Obs	81	37		
		Mean return (%)	-4.878***	-1.040*	-3.837*	-1.83
	Moody's	#Obs	70	44		
		Mean return (%)	-2.247*	-1.101	-1.147	-0.59
	Fitch	#Obs	96	24		
		Mean return (%)	-3.391**	-0.612	-2.779	-0.86
Credit rating upgrades	Full Sample	#Obs	103	82		
		Mean return (%)	1.197	0.096	1.101	1.26
	S&P	#Obs	43	27		
		Mean return (%)	1.644	0.129	1.515	1.06
	Moody's	#Obs	37	22		
		Mean return (%)	-0.206	-0.055	-0.151	-0.51
	Fitch	#Obs	23	33		
		Mean return (%)	2.619	0.171	2.449	1.06

*Stock market reaction (mean abnormal return) to rating announcements throughout the US sample during the period 1st January 2006 to 1st June 2016. The sample compares rating announcements before and after the introduction of the regulation separately for each CRA. Post start date is 21st July 2010. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table 4.10: Information content – OLS model

Panel A: Downgrades

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.152***	-2.92	-0.177**	-2.54	-0.205***	-5.71	-0.096	-1.24
Rating Downgrade	-3.982***	-5.47	-2.412**	-2.12	-5.060***	-4.54	-4.226***	-3.04
Post × Rating Downgrade	2.958**	2.47	1.160	0.56	4.025***	3.19	3.625**	2.34
Moody's	-0.006	-0.35						
Fitch	-0.053	-1.61						
ROAA	-0.188**	-2.22	-0.214***	-3.31	-0.230**	-2.19	-0.189	-1.49
CIR	-0.002	-0.65	0.001	1.17	-0.001	-0.45	-0.005	-1.12
LLPNIR	-0.001	-0.36	0.006***	2.63	-0.002	-0.95	-0.004	-0.90
Ln(TA)	0.045	1.54	0.012	0.52	0.020	0.87	0.091*	1.70
NIIGR	-0.003	-1.09	-0.003	-1.56	-0.0001	-0.04	-0.007	-1.23
ETA	0.039*	1.88	0.033**	2.59	0.016	1.18	0.073	1.66
LAtoCSTF	0.0001	0.09	-0.001	-0.52	-0.001	-1.57	0.003	0.93
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	459,939		134,519		146,911		178,509	
Pseudo R^2	0.31%		0.25%		0.43%		0.34%	

Panel B: Upgrades

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.151***	-2.90	-0.177**	-2.54	-0.202***	-5.70	-0.094	-1.22
Rating Upgrade	1.258	1.10	-0.348*	-1.91	1.843*	1.67	2.657	0.89
Post × Rating Upgrade	-1.112	-0.96	0.284	1.33	-1.649	-1.45	-2.417	-0.81
Moody's	-0.005	-0.28						
Fitch	-0.048	-1.45						
ROAA	-0.183**	-2.15	-0.214***	-3.26	-0.227**	-2.18	-0.183	-1.41
CIR	-0.002	-0.71	0.001	1.12	-0.002	-0.58	-0.005	-1.15
LLPNIR	-0.001	-0.50	0.006**	2.50	-0.002	-1.11	-0.004	-0.99
Ln(TA)	0.044	1.46	0.011	0.46	0.016	0.66	0.090*	1.67
NIIGR	-0.003	-1.05	-0.003	-1.51	-0.0001	-0.05	-0.007	-1.17
ETA	0.039*	1.86	0.034**	2.61	0.016	1.22	0.071	1.61
LAtoCSTF	0.0001	0.11	-0.001	-0.50	-0.001	-1.51	0.003	0.91
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	459,939		134,519		146,911		178,509	
Pseudo R^2	0.21%		0.21%		0.24%		0.25%	

The table presents the results of Eq. (4.7). The dependent variable is AR, the abnormal stock return and is calculated as shown in Eq. (4.6). ***Rating upgrade*** *and* ***Rating downgrade*** *are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise. Only cases with the full window [-230, -30] are considered.* ***Post*** *is a dummy variable that takes the value of 1 after 21st July 2010 and zero otherwise.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions see Table 4.2. The Sample includes US FIs during the period January 2006 to June 2016 in the 27 EU countries.* ***Post****,* ***Rating downgrade*** *and* ***Rating upgrade****,* ***Post * Rating downgrade****,* ***Post* Rating upgrade*** *are multiplied by 100 to give the impact on the percentage abnormal return. Standard errors are clustered by company and a full set of* ***state*year dummies*** *are included. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table 4.11: EU regulation

Panel A: Eq. (4.2)

	Combined		Moody's		S&P		Fitch	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.015	-0.62	-0.089***	-3.86	0.032	0.35	0.036	1.10
EU post	0.005	0.24	-0.068**	-2.17	-0.003	-0.06	0.046	1.32
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	65,495		17,173		20,086		28,236	
Pseudo R^2	11.70%		14.90%		11.70%		13.40%	

Panel B: Eq. (4.3)

	Combined		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.033	-1.30	-0.071***	-3.33	-0.005	-0.06
EU post	-0.005	-0.16	-0.044	-1.61	0.048	1.04
FMS	-4.838***	-4.75	-5.025***	-3.94	-4.452***	-3.86
Post * FMS	-0.010	-0.12	-0.082	-1.15	0.140	0.52
EU post * FMS	-0.174**	-2.21	-0.113	-1.04	-0.276**	-2.15
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
Observations	37,259		17,173		20,086	
Pseudo R^2	12.40%		14.90%		11.70%	

Panel C: Eq. (4.4)

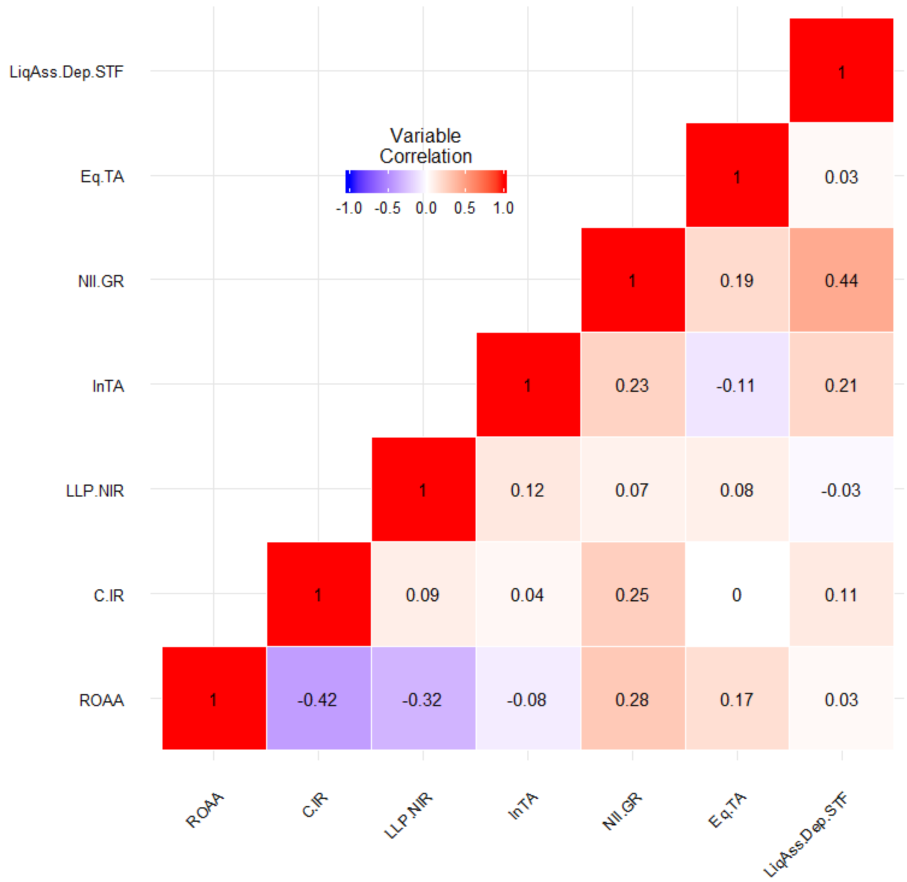
	Combined		Moody's		S&P		Fitch	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.112	-1.07	-0.125	-0.85	0.007	0.13	-0.093	-0.44
EU post	0.009	0.15	0.000	0.00	-0.109	-0.80	0.060	0.57
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	34,893		5,163		5,631		12,135	
Pseudo R^2	28.20%		19.90%		25.50%		31.80%	

Panel D: Eq. (4.5)

	Combined		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.064	-0.72	-0.318	-0.87	0.019	0.34
EU post	-0.072	-0.73	0.000	0.00	-0.135	-0.80
FMS	-3.881**	-2.21	-3.879**	-2.02	-3.240**	-2.20
Post * FMS	0.037	0.35	0.318	0.87	-0.050	-0.32
EU post * FMS	0.072	0.73	-0.000	-0.00	0.135	0.80
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
Observations	13,448		5,163		5,631	
Pseudo R^2	24.10%		19.90%		25.50%	

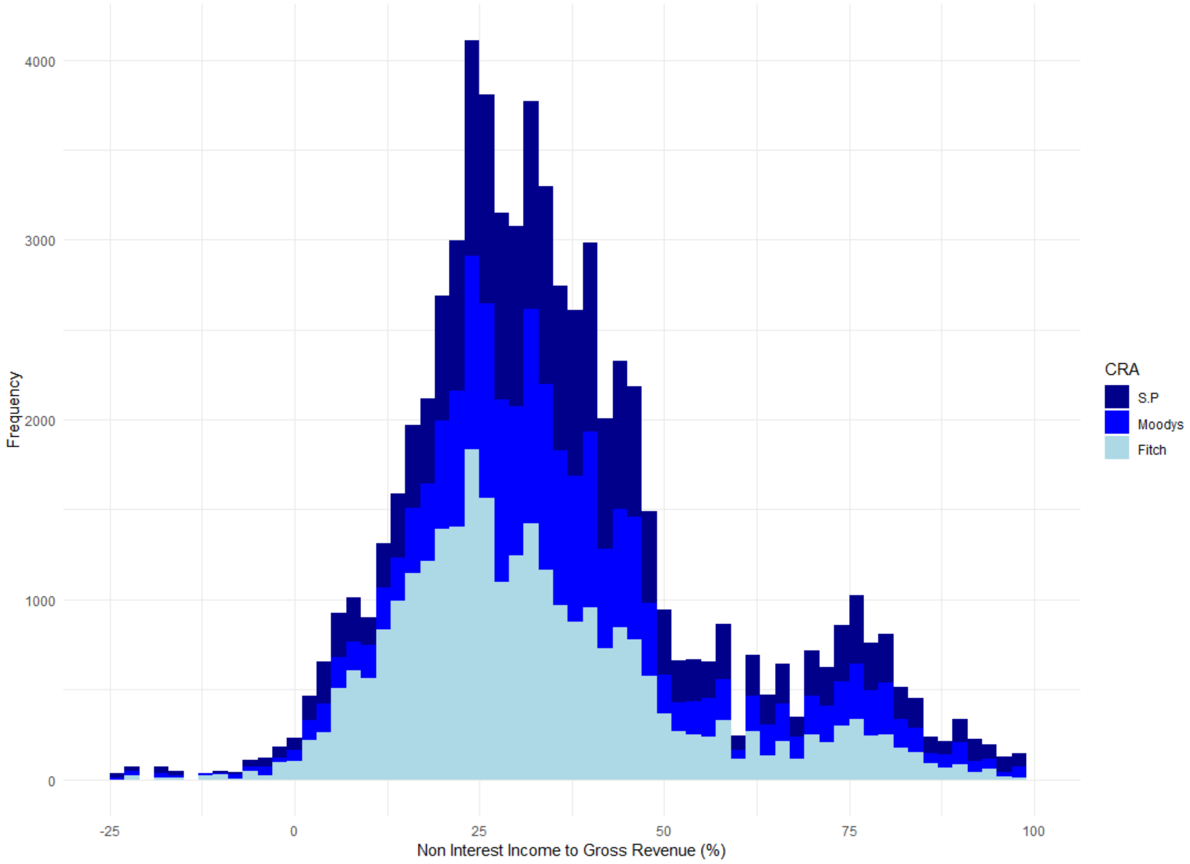
The table shows the ordered logit regression results for Eq. (4.2) and Eq. (4.3) (rating levels) and logit regressions Eq. (4.4) and Eq. (4.5) (false warnings) between January 2006 and June 2016. In Eq. (4.2) and (4.3) the dependent variable is the 52-point CCR scale and in Eq. (4.4) and (4.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise. ***Post*** *start date is 21st July 2010.* ***EU Post*** *takes the value of one after 1st July 2011 and zero otherwise. The standard errors are clustered by FI and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Figure 4.1: Control variable correlation matrix



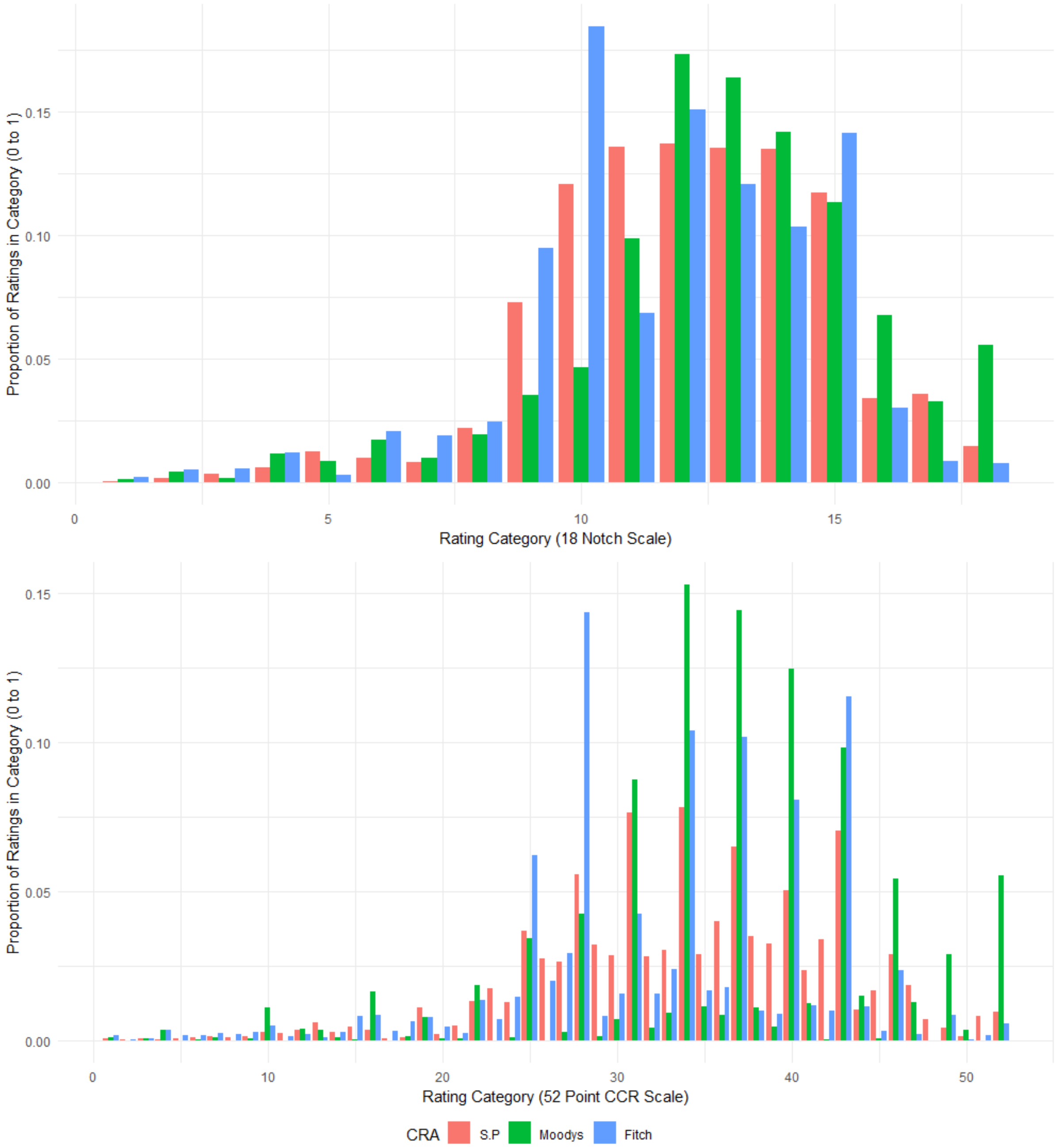
Correlation matrix for the banking variables listed in Table 4.2.

Figure 4.2: NII-GR distribution



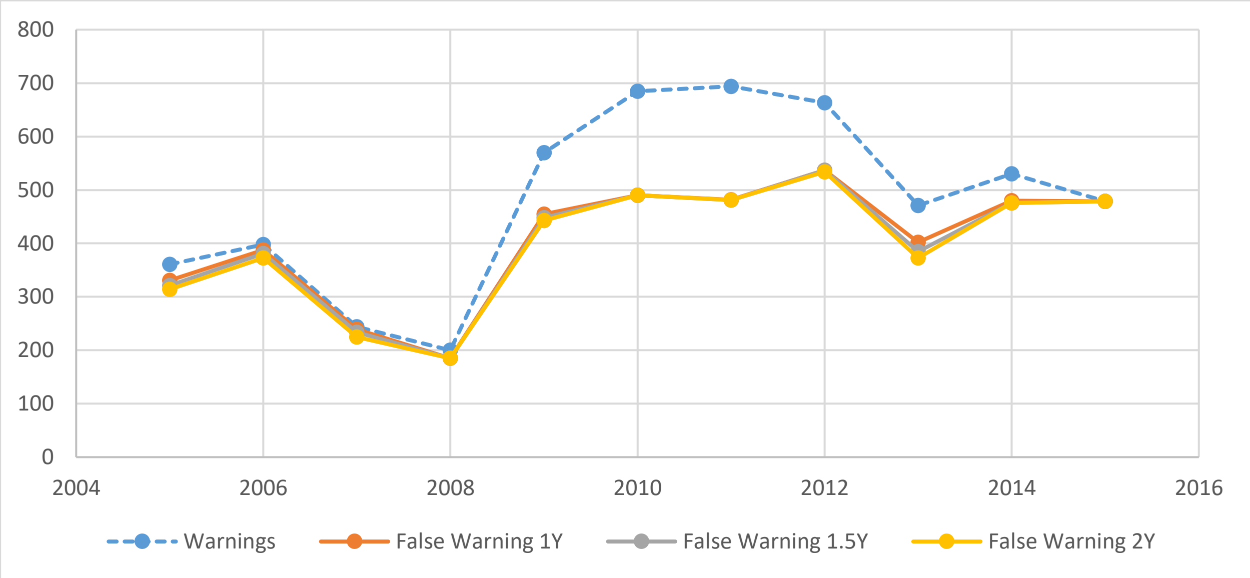
Distribution of Non-Interest Income to Gross Revenue (%) for FIs in the sample. This represents the portion of income that comes from interest income (traditional banking activities e.g. loans) and from non-interest income (e.g. fees).

Figure 4.3: Distribution of ratings



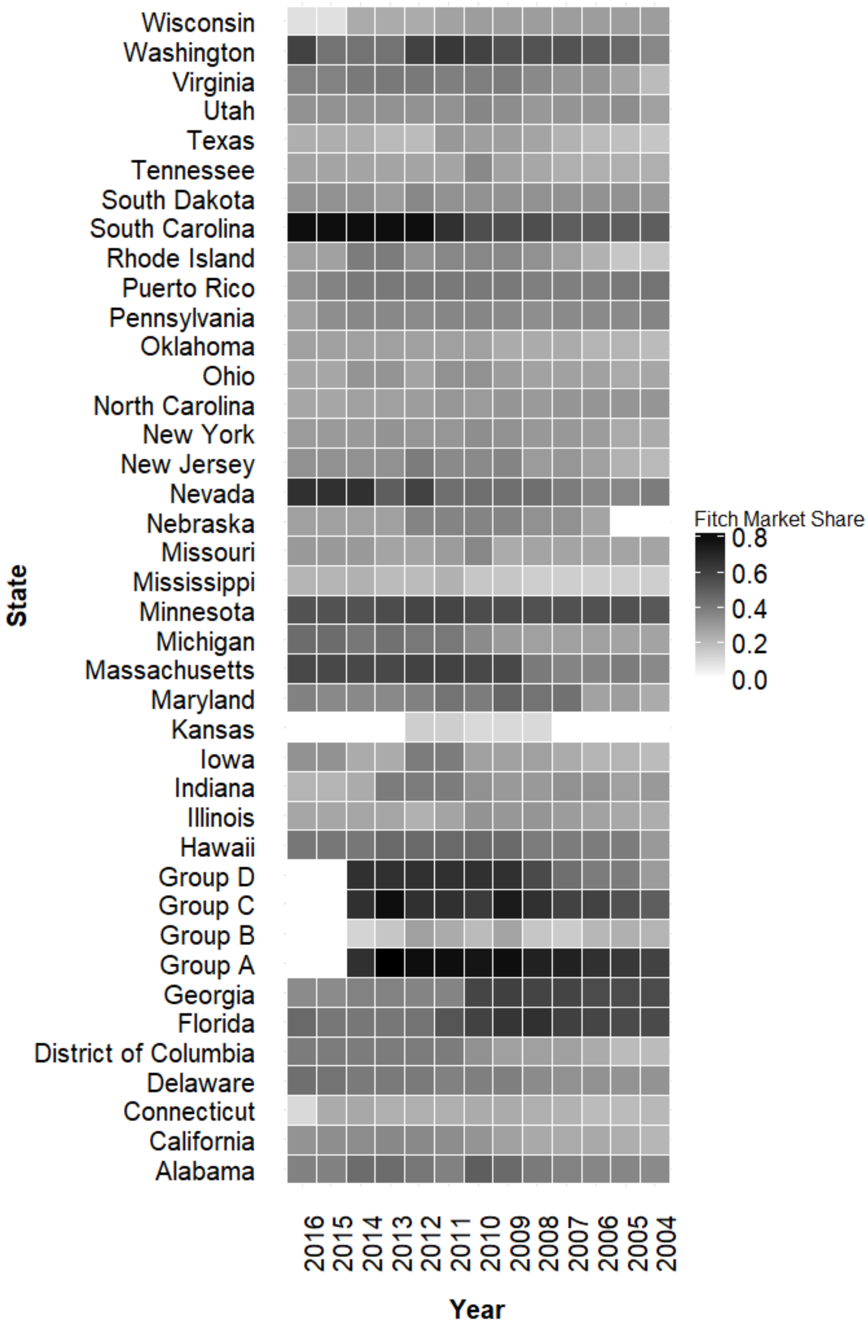
The distribution of ratings in each rating category in the US sample from January 2006 to June 2016. The top graph shows the 18-notch scale and the lower the 52 point CCR scale.

Figure 4.4: Incidence of false warnings



The graph includes false warnings on three timescales (no default after 12, 18 and 24 months) in addition to the number of warnings issued by the CRAs. The US regulation comes into effect in July 2010.

Figure 4.5: Fitch market share distribution



Variation of Fitch market share over state and year in the US sample.

APPENDIX 4.I – SUPPORTING TABLES

Table A. 4.1: Rating scale and frequency

S&P		Moody's		Fitch	
Rating Category	Frequency	Rating Category	Frequency	Rating Category	Frequency
AAA	312	Aaa	1,049	AAA	216
AA+	778	Aa1	619	AA+	239
AA	733	Aa2	1,280	AA	847
AA-	2,546	Aa3	2,149	AA-	3,982
A+	2,932	A1	2,686	A+	2,915
A	2,941	A2	3,109	A	3,404
A-	2,973	A3	3,288	A-	4,257
BBB+	2,946	Baa1	1,874	BBB+	1,930
BBB	2,620	Baa2	882	BBB	5,201
BBB-	1,580	Baa3	670	BBB-	2,673
BB+	479	Ba1	368	BB+	690
BB	180	Ba2	186	BB	532
BB-	210	Ba3	321	BB-	580
B+	273	B1	158	B+	79
B	124	B2	222	B	338
B-	70	B3	29	B-	150
CCC+/CCC/CCC-	36	Caa1/Caa2/Caa3	77	CCC	146
CC/C/SD	6	Ca/C/D	21	CC/C/D	57
Total	21,739	Total	18,988	Total	28,236

Panel A shows the mapping of ratings to the 18 notch and the 52-point CCR scale. In the CCR scale positive and negative watch signals award +2/-2 points respectively and a positive and negative outlook award +1/-1 point respectively. Panel B shows the frequency of occurrences of ratings in different categories throughout the monthly US sample.

Table A. 4.2: Occurrences of false warnings

	FIs with Warnings	FW 1 Year	FW 1.5 Year	FW 2 Year	S&P	Moody's	Fitch
Alabama	6	6	6	6	1	3	4
Alaska	0	0	0	0	0	0	0
American Samoa	0	0	0	0	0	0	0
Arizona	1	1	1	1	0	1	0
Arkansas	0	0	0	0	0	0	0
California	17	14	13	13	8	10	5
Colorado	1	1	1	1	0	0	1
Connecticut	1	1	1	1	1	0	0
Delaware	2	1	1	1	0	1	1
District of Columbia	1	1	1	1	1	0	1
Florida	10	9	9	9	0	0	9
Georgia	11	9	9	9	3	2	8
Guam	0	0	0	0	0	0	0
Hawaii	2	2	2	2	0	0	2
Idaho	0	0	0	0	0	0	0
Illinois	6	6	6	6	0	2	4
Indiana	1	1	1	1	1	1	1
Iowa	1	1	1	1	1	0	1
Kansas	0	0	0	0	0	0	0
Kentucky	0	0	0	0	0	0	0
Louisiana	2	0	0	0	0	0	0
Maine	0	0	0	0	0	0	0
Maryland	2	2	2	2	2	2	1
Massachusetts	2	2	2	2	0	0	2
Michigan	5	5	5	5	4	5	4
Minnesota	0	0	0	0	0	0	0
Mississippi	0	0	0	0	0	0	0
Missouri	0	0	0	0	0	0	0
Montana	0	0	0	0	0	0	0
Nebraska	4	4	4	4	0	1	3
Nevada	2	2	2	2	0	2	0
New Hampshire	1	1	1	1	1	1	0
New Jersey	0	0	0	0	0	0	0
New Mexico	0	0	0	0	0	0	0
New York	10	10	10	10	1	2	9
North Carolina	1	0	0	0	0	0	0
North Dakota	0	0	0	0	0	0	0
Ohio	2	1	1	1	0	0	1
Oklahoma	0	0	0	0	0	0	0
Oregon	0	0	0	0	0	0	0
Pennsylvania	2	2	2	2	0	0	2
Puerto Rico	8	8	8	8	5	3	6
Rhode Island	1	1	1	1	1	0	1
South Carolina	1	1	1	1	1	0	1
South Dakota	0	0	0	0	0	0	0
Tennessee	2	1	1	1	1	0	0
Texas	3	3	3	3	2	2	1
Utah	3	3	3	3	1	2	1
Vermont	0	0	0	0	0	0	0
Virgin Islands	0	0	0	0	0	0	0
Virginia	3	3	3	3	2	2	1
Washington	2	1	1	1	0	0	1
West Virginia	0	0	0	0	0	0	0
Wisconsin	4	2	2	2	2	1	0
Wyoming	0	0	0	0	0	0	0
Total	120	105	104	104	39	43	71

The number of false warnings in each state for each CRA. A warning is defined as a period in which a FI is rated BB+ or lower. A false warning is defined as a period in which is rated BB+ or below but does not default in the following 1, 1.5 or 2 years.

Table A. 4.3: Distribution of rating upgrades and downgrades

	CCR (outlook and watch)				Rating level only			
	Negative signals		Positive signals		Downgrades		Upgrades	
Year	#Obs	AR (%)	#Obs	AR (%)	#Obs	AR (%)	#Obs	AR (%)
2006	19	2.297	93	-0.061	6	0.776	28	-0.117
2007	48	-1.010	70	1.220	21	-3.164	49	-0.027
2008	112	-0.079	20	11.852	57	-1.961	7	16.634
2009	190	-3.177	17	0.778	140	-4.260	3	1.216
2010	43	-2.181	47	-1.214	27	-3.805	7	-0.490
2011	43	-0.456	43	-0.193	27	-0.637	16	0.132
2012	35	-0.340	26	0.524	21	0.567	11	0.824
2013	20	-0.838	35	1.201	11	-0.526	13	0.812
2014	20	-4.468	23	0.882	9	-9.944	15	-0.305
2015	44	-0.302	43	1.057	16	-0.184	19	0.079
Before regulation	393	-1.744	217	1.063	239	-3.606	89	1.370
After regulation	181	-0.976	200	0.777	96	-1.191	79	0.111
Total	574	-1.502	417	0.926	335	-2.914	168	0.778

The occurrences of rating upgrades and downgrades throughout the sample. Abnormal Return (AR). The table shows both the CCR scale that takes account of changes in outlook and watch in addition to the rating and changes at the rating level only.

Table A. 4.4: Informational content summary statistics

Variable	Obs	Mean	Std.	Min	Max
Rating	501,234	31.417	9.528	1.000	52.000
Abnormal return	501,234	0.00001	0.029	-1.006	1.283
ROAA	459,939	0.783	1.152	-8.085	4.559
Cost to income ratio	459,939	65.708	23.038	8.412	384.664
LLPNIR	459,939	22.295	38.986	-883.693	500.524
Ln(TA)	459,939	17.688	1.636	13.688	21.908
NII-GR	459,939	38.519	23.870	-109.830	225.980
Eq-TA	459,939	10.466	3.485	-1.758	34.272
Liquid assets to deposits and STF	459,939	15.623	26.391	0.493	464.367

Summary statistics for the rating events and stock returns over the period 1st January 2006 to 1st June 2016. There are 1,538 rating events (including outlook and watch) and 925 (excluding outlook and watch).

Table A. 4.5: Fitch market share – Additional robustness tests

Panel A: Ordered logit - Percentage

Variable	CCR		Notch scale	
	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share percentage (t-1)	31.603***	7.06	30.717***	6.49
Controls included	Yes		Yes	
State * Year FE	Yes		Yes	
# Observations	37,259		37,259	
Pseudo R^2	12.40%		16.70%	

Panel B: Ordered logit - No controls

Variable	Moody's and S&P		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share dummy (t-1)	-2.113***	-3.41	-2.719***	-3.92	-1.421**	-2.00
Controls included	No		No		No	
State * Year FE	Yes		Yes		Yes	
Number of observations	37,259		17,173		20,086	
Pseudo R^2	8.80%		11.20%		8.90%	

Panel C: Ordered probit

Variable	Moody's and S&P		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share dummy (t-1)	-2.587***	-5.48	-2.797***	-4.84	-2.402***	-4.99
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
Number of observations	37,259		17,173		20,086	
Pseudo R^2	11.60%		14.20%		11.80%	

Panel D: Ordered logit – Non-interacted FE

Variable	Moody's and S&P		Moody's		S&P	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share dummy (t-1)	-0.336**	-2.42	-0.308*	-1.77	-0.349**	-2.44
Controls included	Yes		Yes		Yes	
State FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Number of observations	37,259		17,173		20,086	
Pseudo R^2	9.90%		11.30%		10.20%	

Panel E: Fitch market share impact – Alternative cut-offs

Variable	10%		40%	
	Coefficient	Z-stat	Coefficient	Z-stat
Fitch market share dummy (t-1)	-6.056***	-5.39	-4.548***	-4.07
Controls included	Yes		Yes	
State * Year FE	Yes		Yes	
# Observations	37,259		37,259	
Pseudo R^2	12.40%		12.40%	

Ordered logit model of Eq. (4.1) using alternative cut-offs between states with stronger and weaker reputational concerns. The limits of 10% and 40% are used instead. Results of investigating the relationship between Fitch market share (dummy, 1 in lower 10%/40%, 0 in top 90%/60%, lagged by 1 year) on a state basis and the dependent variable is the FI credit rating (52 point CCR scale) in the EU sample during the period 2006 to 2016. Standard errors are clustered by FI and ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.6: Rating levels - Ordered probit and OLS

Panel A: Eq. (4.2) – Ordered probit

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.008	-0.63	-0.044***	-3.44	-0.008	-0.39	0.022	1.06
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	65,495		17,173		20,086		28,236	
Pseudo R^2	11.00%		14.20%		11.80%		12.30%	

Panel B: Eq. (4.3) – Ordered probit

	Full Sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.018	-1.61	-0.032**	-2.56	-0.006	-0.33
FMS	-2.587***	-5.48	-2.797***	-4.84	-2.402***	-4.99
Post × FMS	-0.023	-0.56	-0.060	-1.61	-0.008	-0.12
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
# Observations	36,259		17,173		20,086	
Pseudo R^2	11.60%		14.20%		11.80	

Panel C: Eq. (4.2) – OLS

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.025	-0.28	-0.237***	-2.99	-0.093	-0.68	0.124	0.94
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	65,495		17,173		20,086		28,236	
Pseudo R^2	50.50%		52.50%		53.90%		53.70%	

Panel D: Eq. (4.3) – OLS

	Full Sample		Moody's		S&P	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.086	-1.15	-0.178**	-2.04	-0.007	-0.06
FMS	-14.587***	-5.58	-16.290***	-4.82	-12.902***	-5.16
Post × FMS	-0.316	-1.11	-0.299	-1.49	-0.380	-0.85
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
# Observations	36,259		17,173		20,086	
Pseudo R^2	52.10%		52.50%		53.90%	

Ordered probit and OLS estimations of Eq. (4.2) and Eq. (4.3) for the US sample which includes ratings by S&P, Moody's and Fitch in Eq. (4.2) (Moody's and S&P in Eq. (4.3)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. The start date is 21st July 2010. In Eq. (4.2) and Eq. (4.3) the dependent variable is credit rating (on a 52-point CCR scale.* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and* ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.7: False warnings – Probit and OLS

Panel A: Eq. (4.4) – Probit

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.069	-1.19	-0.073	-0.93	0.002	0.06	-0.073	-0.62
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	34,893		5,163		21,739		12,135	
Pseudo R^2	28.50%		20.00%		53.10%		31.90%	

Panel C: Eq. (4.5) – Probit

	Full Sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.038	-0.75	-0.164	-0.93	0.008	0.24
Fitch market share	-2.101**	-2.40	-2.133**	-2.26	-1.710**	-2.56
Post × Fitch market share	0.023	0.38	0.164	0.93	-0.026	-0.25
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
# Observations	13,448		5,163		5,631	
Pseudo R^2	24.30%		20.00%		25.80%	

Panel A: Eq. (4.4) – OLS

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.009*	-1.76	-0.004	-0.80	-0.001	-0.18	-0.015	-1.35
Controls included	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	68,963		18,988		21,739		28,236	
Pseudo R^2	26.10%		32.00%		28.60%		34.90%	

Panel C: Eq. (4.5) – OLS

	Full Sample		Moody's		S&P	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.004	-0.84	-0.008	-0.80	-0.002	-0.40
Fitch market share	0.134**	2.08	0.169*	1.70	0.096*	1.68
Post × Fitch market share	0.004	0.68	0.008	0.80	0.002	0.33
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
# Observations	40,727		18,988		21,739	
Pseudo R^2	27.90%		32.00%		28.60%	

Probit and OLS estimation of Eq. (4.4) and Eq. (4.5) for the US sample which includes ratings by S&P, Moody's and Fitch (Moody's and S&P in Eq. (4.4) and Eq. (4.5)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. Post start date is 21st July 2010. In Eq. (4.4) and Eq. (4.5) the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise.* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and ***, **, * represent significance beyond the* 1^{st}, 5^{th} *and* 10^{th} *percentile levels respectively.*

Table A. 4.8: Rating levels - Alternative 18-notch rating scale

Panel A: Combined sample

	Eq. (4.2)		Eq. (4.3)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.047*	-1.99	-0.059**	-2.76
FMS			-4.893***	-4.38
Post × FMS			-0.01	-0.11
Moody's	0.775***	7.84	0.796***	7.32
Fitch	0.096	1.01		
ROAA	-0.254	-1.5	-0.266	-1.17
CIR	-0.045***	-4.31	-0.043***	-3.35
LLPNIR	-0.025***	-3.63	-0.029**	-3.26
Ln(TA)	0.565***	7.81	0.586***	4.64
NIIGR	0.018	1.93	0.008	0.61
ETA	0.044*	1.96	0.033	0.98
LAtoCSTF	0.022**	2.89	0.020*	2.01
State * Year FE	Yes		Yes	
# Observations	65,495		37,259	
Pseudo R^2	15.61%		16.70%	

Panel B: Eq. (4.2) – Separate CRAs

	Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.090***	-3.94	-0.063	-0.81	-0.012	-0.36
Controls included	Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes	
# Observations	17,173		20,086		28,236	
Pseudo R^2	17.20%		18.60%		17.50%	

Panel C: Eq. (4.3) – Separate CRAs

	Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.071***	-3.45	-0.074	-0.98
FMS	-4.948***	-3.84	-4.797***	-3.57
Post × FMS	-0.089	-1.22	-0.034	-0.15
Controls included	Yes		Yes	
State * Year FE	Yes		Yes	
# Observations	17,173		20,086	
Pseudo R^2	17.20%		18.40%	

Ordered logit estimations of Eq. (4.2) and Eq. (4.3) for the US sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (4.3)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. The start date is 21st July 2010. In Eq. (4.2) and Eq. (4.3) the dependent variable is credit rating (on an 18-notch rating scale).* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and* ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.9: Alternative definitions of false warnings

Panel A: Using B+

	Eq. (4.4)		Eq. (4.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.014	-0.07	-0.215	-1.07
FMS			-1.596	-0.75
Post × FMS			0.503**	2.18
Moody's	-0.139	-0.52	-0.128	-0.50
Fitch	-0.367	-1.03		
ROAA	0.158	0.67	0.106	0.35
CIR	0.058***	3.79	0.055**	2.30
LLPNIR	0.025***	2.68	0.029***	2.63
Ln(TA)	-0.668***	-3.19	-0.362	-1.20
NIIGR	0.008	0.69	0.016	1.02
ETA	-0.200***	-3.62	-0.090	-1.33
LAtoCSTF	0.002	0.23	0.005	0.36
State * Year FE	Yes		Yes	
# Observations	19,279		8,097	
Pseudo R^2	33.20%		26.50%	

Panel B: 2 year duration

	Eq. (4.4)		Eq. (4.5)	
Variable	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.108	-1.05	-0.066	-0.75
FMS			-3.563**	-2.08
Post × FMS			0.036	0.35
Moody's	0.121	0.59	0.110	0.51
Fitch	0.308	1.47		
ROAA	0.180	1.09	0.155	0.69
CIR	0.027***	2.64	0.013	0.83
LLPNIR	0.030***	4.65	0.038***	4.36
Ln(TA)	-0.514***	-4.65	-0.493**	-2.52
NIIGR	-0.009	-0.92	-0.003	-0.26
ETA	-0.080**	-2.04	-0.103**	-2.53
LAtoCSTF	0.007	0.71	0.020*	1.84
State * Year FE	Yes		Yes	
# Observations	34,262		13,364	
Pseudo R^2	27.40%		23.70%	

Logit regression for the US sample which includes ratings by S&P, Moody's and Fitch (Moody's and S&P for Eq. (4.5)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. Post start date is 21st July 2010. In panel A The dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of B+ or below does not default after one year and zero otherwise. In panel B the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after two years and zero otherwise.* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by FI and* ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.10: Rating levels – State and year FE

Panel A: Eq. (4.2) - State and year no interactions

	Full sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.0004	-0.02	-0.079***	-4.17	0.017	0.54	0.069*	1.66
Controls included	Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# Observations	65,495		17,173		20,086		28,236	
Pseudo R^2	9.30%		11.20%		10.20%		10.40%	

Panel B: Eq. (4.3) - State and year no interactions

	Full sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.165***	-2.64	-0.228***	-3.31	-0.113	-1.53
FMS	-0.634***	-3.03	-0.668**	-2.55	-0.600***	-2.75
Post × FMS	0.575**	2.57	0.671***	2.58	0.494**	2.01
Controls included	Yes		Yes		Yes	
State FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
# Observations	37,259		17,173		20,086	
Pseudo R^2	9.90%		11.40%		10.30%	

Ordered logit estimations of Eq. (4.2) and Eq. (4.3) for the US sample which includes ratings by S&P, Moody's and Fitch (Moody's and Fitch in Eq. (4.3)). ***Post*** *is a dummy variable that is 1 after the enactment of the regulation and zero otherwise. The start date is 21st July 2010. In Eq. (4.2) and Eq. (4.3) the dependent variable is credit rating (on an 18-notch rating scale).* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Standard errors are clustered by company and state and year interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.11: False warnings - No state and year interactions

Panel B: Eq. (4.4) – Separate CRAs

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	-0.136	-1.37	-0.065	-0.65	-0.100	-1.05	-0.250	-1.32
Moody's	0.117	0.62						
Fitch	0.257	1.26						
ROAA	0.186	1.24	0.090	0.42	0.113	0.55	0.235	1.27
CIR	0.026***	2.72	0.004	0.29	0.011	0.75	0.044***	4.09
LLPNIR	0.026***	4.03	0.029***	2.89	0.030***	3.81	0.020***	2.68
Ln(TA)	-0.426***	-5.56	-0.402**	-2.38	-0.506***	-2.88	-0.531***	-4.91
NIIGR	-0.008	-0.91	-0.001	-0.06	0.002	0.12	-0.008	-0.94
ETA	-0.060*	-1.73	-0.067	-1.57	-0.087**	-2.05	-0.051	-1.27
LAtoCSTF	0.008	0.76	0.016	1.45	0.026***	2.82	0.004	0.33
State FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# Observations	56,206		10,075		12,589		21,569	
Pseudo R^2	26.20%		24.70%		26.40%		31.40%	

Panel C: Eq. (4.5) – Separate CRAs

	Full Sample		Moody's		S&P	
Variable	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Post	0.216	1.01	0.393	1.49	0.053	0.20
FMS	1.335***	3.19	1.450***	3.04	1.240**	2.44
Post × FMS	-0.739	-1.47	-1.001	-1.87	-0.356	-0.55
Moody's	0.128	0.65				
ROAA	0.116	0.64	0.092	0.43	0.118	0.56
CIR	0.009	0.71	0.004	0.29	0.013	0.83
LLPNIR	0.029***	3.74	0.028***	2.68	0.031***	3.82
Ln(TA)	-0.458***	-3.64	-0.397**	-2.16	-0.523***	-3.24
NIIGR	0.001	0.08	0.001	0.06	0.003	0.21
ETA	-0.086**	-2.18	-0.081*	-1.76	-0.101**	-2.09
LAtoCSTF	0.021**	2.10	0.015	1.33	0.027***	2.59
State FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
# Observations	26,141		10,075		12,589	
Pseudo R^2	27.10%		26.10%		27.70%	

Logit regression of false warnings for the US sample which includes ratings by S&P, Moody's and Fitch (Moody's and S&P in Eq. (4.5)). ***Post*** *start date is 21st July 2010 and the dependent variable is a dummy representing false warnings, it takes the value of 1 if a rating of BB+ or below does not default after one year and zero otherwise.* ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Results for the logit model using state and year dummies with no interactions. Standard errors are clustered by company and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.12: Informational content – Clustered vs independent events

Upgrade/downgrade	Sample	Variable	Post = 0	Post = 1	Difference (Before-After)	T-statistic
Credit rating downgrades	Whole sample	#Obs	247	105		
		Mean return (%)	-3.555***	-0.968	-2.587*	-1.88
	Independent events	#Obs	155	90		
		Mean return (%)	-2.046**	0.033	-2.079*	-1.81
	Clustered events	#Obs	92	15		
		Mean return (%)	-6.096***	-6.974	0.878	0.19
Credit rating upgrades	Whole sample	#Obs	103	82		
		Mean return (%)	1.197	0.096	1.101	1.26
	Independent events	#Obs	80	61		
		Mean return (%)	0.081	0.202	-0.122	-0.51
	Clustered events	#Obs	23	21		
		Mean return (%)	5.081	-0.211	5.292	1.51

Stock market reaction (mean abnormal return) to rating announcements throughout the US sample during the period 1st January 2006 to 1st June 2016. The sample compares rating announcements before and after the introduction of the regulation and distinguishes between independent and clustered events. ***Post*** *start date is 21st July 2010. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.13: Informational content – OLS model - Clustering

Panel A: Rating downgrades – Including clusters

	Whole sample		Moody's		S&P		Fitch	
	Coeff	t stat	Coeff	t stat	Coeff	t stat	Coeff	t stat
Post	-0.152***	-2.92	-0.177**	-2.54	-0.205***	-5.71	-0.096	-1.24
Rating notch downgrade	-3.982***	-5.47	-2.412**	-2.12	-5.060***	-4.54	-4.226***	-3.04
Post # Rating notch downgrade	2.958**	2.47	1.160	0.56	4.025***	3.19	3.625**	2.34
Controls	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	459,939		134,519		146,911		178,509	
Adjusted R^2	0.31%		0.25%		0.43%		0.34%	

Panel B: Rating downgrades – Excluding clusters

	Whole sample		Moody's		S&P		Fitch	
	Coeff	t stat	Coeff	t stat	Coeff	t stat	Coeff	t stat
Post	-0.150***	-2.94	-0.175**	-2.54	-0.200 ***	-5.92	-0.095	-1.24
Rating notch downgrade	-2.540***	-2.84	-2.793**	-2.54	-2.276*	-1.97	-2.569	-1.48
Post # Rating notch downgrade	2.560***	2.78	3.075***	2.73	1.551	1.34	3.148 *	1.75
Controls	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	459,312		134,315		146,695		178,302	
Adjusted R^2	0.23%		0.24%		0.25%		0.27%	

Panel C: Rating upgrades – Including clusters

	Whole sample		Moody's		S&P		Fitch	
	Coeff	t stat	Coeff	t stat	Coeff	t stat	Coeff	t stat
Post	-0.151***	-2.90	-0.177**	-2.54	-0.202***	-5.70	-0.094	-1.22
Rating notch downgrade	1.258	1.10	-0.348*	-1.91	1.843*	1.67	2.657	0.89
Post # Rating notch downgrade	-1.112	-0.96	0.284	1.33	-1.649	-1.45	-2.417	-0.81
Controls	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	459,939		134,519		146,911		178,509	
Adjusted R^2	0.31%		0.25%		0.43%		0.34%	

Panel D: Rating upgrades – Excluding clusters

	Whole sample		Moody's		S&P		Fitch	
	Coeff	t stat	Coeff	t stat	Coeff	t stat	Coeff	t stat
Post	-0.149***	-2.92	-0.174**	-2.53	-0.199***	-5.93	-0.095	-1.23
Rating notch downgrade	0.079	0.49	-0.430*	-1.93	0.462*	1.68	0.181	0.57
Post # Rating notch downgrade	0.123	0.44	0.301	1.01	-0.148	-0.31	0.109	0.28
Controls	Yes		Yes		Yes		Yes	
State * Year FE	Yes		Yes		Yes		Yes	
Observations	459,312		134,315		146,695		178,302	
Adjusted R^2	0.21%		0.21%		0.22%		0.27%	

Post *start date is a dummy variable that takes the value of one after 21st July 2010 and zero otherwise. OLS regression of abnormal returns for the US sample which includes ratings by S&P, Moody's and Fitch.* ***Post***, ***rating downgrade***, ***upgrade*** *and the interactions are multiplied by 100 to give the impact on the percentage abnormal return.* ***Rating upgrade*** *and* ***downgrade*** *are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise. Only cases with the full window [-230, -30] are considered. Standard errors are clustered by FI and* ***state*year*** *interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

Table A. 4.14: Information content – OLS model – Including outlook and watch

Panel A: Negative signals

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.152***	-2.92	-0.177**	-2.54	-0.203***	-5.71	-0.096	-1.24
Rating Downgrade	-1.870***	-3.22	-2.164*	-1.95	-1.332	-1.31	-2.172**	-2.35
Post × Rating Downgrade	1.183	1.65	1.511	0.97	0.267	0.25	1.946*	1.91
Moody's	-0.011	-0.60						
Fitch	-0.052	-1.56						
ROAA	-0.187**	-2.19	-0.215***	-3.29	-0.228**	-2.19	-0.190	-1.48
CIR	-0.002	-0.69	0.001	1.13	-0.002	-0.53	-0.005	-1.15
LLPNIR	-0.001	-0.42	0.006**	2.64	-0.002	-1.05	-0.004	-0.92
Ln(TA)	0.045	1.52	0.012	0.52	0.020	0.82	0.091*	1.69
NIIGR	-0.003	-1.04	-0.003	-1.54	-0.000	-0.02	-0.007	-1.17
ETA	0.039*	1.85	0.033**	2.58	0.015	1.15	0.073	1.64
LAtoCSTF	0.000	0.06	-0.001	-0.53	-0.001	-1.57	0.002	0.89
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	459,939		134,519		146,911		178,509	
Pseudo R^2	0.17%		0.25%		0.53%		0.98%	

Panel B: Positive signals

	Full Sample		Moody's		S&P		Fitch	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Post	-0.151***	-2.91	-0.178**	-2.55	-0.202***	-5.69	-0.094	-1.21
Rating Upgrade	1.061	1.15	-1.226	-1.03	1.372	1.38	1.895	1.21
Post × Rating Upgrade	-0.459	-0.42	2.183	1.31	-1.124	-0.87	-1.189	-0.72
Moody's	-0.001	-0.05						
Fitch	-0.047	-1.44						
ROAA	-0.182**	-2.14	-0.212***	-3.20	-0.226**	-2.17	-0.184	-1.42
CIR	-0.002	-0.73	0.001	1.11	-0.002	-0.61	-0.005	-1.18
LLPNIR	-0.001	-0.51	0.006**	2.49	-0.003	-1.13	-0.004	-1.00
Ln(TA)	0.044	1.47	0.009	0.40	0.015	0.63	0.090*	1.68
NIIGR	-0.003	-1.07	-0.003	-1.50	-0.000	-0.04	-0.007	-1.19
ETA	0.039*	1.86	0.033**	2.57	0.017	1.25	0.071	1.61
LAtoCSTF	0.000	0.14	-0.000	-0.47	-0.001	-1.52	0.003	0.94
State * Year FE	Yes		Yes		Yes		Yes	
# Observations	459,939		134,519		146,911		178,509	
Pseudo R^2	0.14%		0.00%		0.04%		0.07%	

The table presents the results of Eq. (4.7) including outlook and watch signals. The dependent variable is AR, the abnormal stock return and is calculated as shown in Eq. (4.6). ***Rating upgrade*** *and* ***Rating downgrade*** *are dummy variables with a value one for a positive signal and negative signal (respectively) and zero otherwise. Only cases with the full window [-230, -30] are considered.* ***Post*** *is a dummy variable that takes the value of 1 after 21st July 2010 and zero otherwise.* ***Moody's*** *and* ***Fitch*** *are dummy variables that take the value of 1 if the rating is issued by them and zero otherwise (if both are zero this indicates a rating by S&P). For control variables' definitions see Table 4.2. The Sample includes US FIs during the period January 2006 to June 2016 in the 27 EU countries.* ***Post****,* ***Rating downgrade*** *and* ***Rating upgrade****,* ***Post* Rating downgrade****,* ***Post* Rating upgrade*** *are multiplied by 100 to give the impact on the percentage abnormal return. Standard errors are clustered by company and a full set of* ***state*year dummies*** *are included. ***, **, * represent significance at 1%, 5% and 10% levels respectively.*

Table A. 4.15: Information content – OLS model – State – Year not interacted

	Rating Downgrades		Rating Upgrades	
Variable	Coefficient	t-stat	Coefficient	t-stat
Post	-0.147***	-2.70	-0.145***	-2.68
Rating Downgrade	-3.996***	-5.48		
Rating Upgrade			1.249	1.09
Post × Rating Downgrade	2.994**	2.52		
Post × Rating Upgrade			-1.097	-0.95
Moody's	-0.018	-0.76	-0.017	-0.67
Fitch	-0.054	-1.64	-0.048	-1.46
ROAA	-0.163*	-1.92	-0.153*	-1.80
CIR	0.001	0.25	0.001	0.23
LLPNIR	-0.002	-0.73	-0.002	-0.82
Ln(TA)	0.052	1.64	0.050	1.56
NIIGR	-0.005	-1.60	-0.005	-1.58
ETA	0.034	1.53	0.033	1.53
LAtoCSTF	0.001	0.83	0.001	0.82
# Observations	459,939		459,939	
Pseudo R^2	0.23%		0.13%	

*Post start date is a dummy variable that takes the value of one after 21st July 2010 and zero otherwise. OLS regression of abnormal returns for the US sample which includes ratings by S&P, Moody's and Fitch. Post, rating downgrade, upgrade and the interactions are multiplied by 100 to give the impact on the percentage abnormal return. All the control variable coefficients are multiplied by 1000 for readability (Moody's and below in the table). Rating upgrade and downgrade are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise. Only cases with the full window [-230, -30] are considered. Standard errors are clustered by company and state and year interactions are included and ***, **, * represent significance beyond the* 1^{st}*,* 5^{th} *and* 10^{th} *percentile levels respectively.*

Table A. 4.16: Information content – OLS model – Fitch market share

	Rating Downgrades		Rating Upgrades	
Variable	Coefficient	t-stat	Coefficient	t-stat
Post	-0.208***	-3.53	-0.206***	-3.51
Rating Downgrade	-4.379***	-5.08		
Rating Upgrade			0.424**	2.09
Fitch market share	-0.079	-0.94	-0.074	-0.88
Rating Downgrade × FMS	1.156	0.74		
Rating Upgrade × FMS			1.761	0.75
Post × FMS	0.136	1.25	0.135	1.25
Post × Rating Downgrade	2.549	-1.47		
Post × Rating Upgrade			-0.164	-0.65
Post × Rating Downgrade × FMS	0.987	0.45		
Post × Rating Upgrade × FMS			-2.233	-0.92
Moody's	-0.007	-0.38	-0.005	-0.27
Fitch	-0.054	-1.63	-0.048	-1.47
ROAA	-0.188**	-2.21	-0.183**	-2.14
CIR	-0.002	-0.64	-0.002	-0.70
LLPNIR	-0.001	-0.38	-0.001	-0.52
Ln(TA)	0.046	1.57	0.044	1.47
NIIGR	-0.003	-1.10	-0.003	-1.05
ETA	0.039*	1.89	0.039*	1.86
LAtoCSTF	0.0001	0.09	0.0001	0.12
# Observations	459,939		459,939	
Pseudo R^2	0.32%		0.22%	

OLS regression of abnormal returns for the US sample which includes ratings by S&P and Moody's. Post, rating downgrade, upgrade and the interactions are multiplied by 100 to give the impact on the percentage abnormal return. All the control variable coefficients are multiplied by 1000 for readability (Moody's and below in the table). Post start date is 21st July 2010. Rating upgrade and downgrade are dummy variables with a value one for an upgrade and downgrade (respectively) and zero otherwise. ***FMS*** *is the Fitch market share dummy that takes the value of 1 in lower 25%, 0 in top 75% and is lagged by 1 year. Only cases with the full window [-230, -30] are considered. Standard errors are clustered by company and state*year interactions are included and ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

The impact of regulatory reforms on European bank behaviour: A dynamic structural estimation

Chapter 5

5.1 INTRODUCTION

Failures of large financial institutions during the 2008 financial crisis exacerbated the crisis, caused significant damage in the real economy and resulted in increased sovereign credit risk (Acharya et al., 2014; Berger et al., 2018). To prevent future repeats, regulators responded with a number of new measures (see Chapter 2). Notable European regulatory efforts were evident in three distinct areas: (i) the European Banking Union, including a bail-in regime, (ii) capital requirement regulations (Basel III) and (iii) reforming credit rating agencies (CRAs). This Chapter builds and estimates a dynamic model of bank behaviour and uses this model to simulate counterfactual scenarios in which these three key regulatory reforms are implemented prior to the financial crisis, thereby enabling investigation of the resultant impact on banks' performance, risk and lending activity.

The first issue of interest is the Single Resolution Mechanism (SRM) of the European Banking Union. Its Bank Recovery and Resolution Directive (BRRD) contains provisions for a bail-in mechanism from 2015. This aims to shift the burden of bank failure from the taxpayer to equity holders and bondholders. Given the potential losses for shareholders in the event of insolvency, there will be an impact on bank decision-making. Secondly, the Basel III common equity capital ratio (CET1), fully implemented by 2019, will increase the amount of equity that banks are required to hold. While this requirement will place a constraint upon banks, it could also impact their risk-taking behaviour. Thirdly, in September 2009, European regulators implemented new regulatory reforms of the credit rating industry. Increased scrutiny and oversight of CRAs led to more conservative ratings (Bannier et al., 2010 and Chapter 3), which will impact banks' behaviour and performance.

With much of the regulation only recently (or yet to be) fully enacted, there is still much debate on its implications. For example, the bail-out of two Italian banks in June 2017 has raised questions on the effectiveness of BRRD and its bail-in regime. Similarly, the optimal capital ratios that banks should adopt to effectively prevent insolvency, as well as the impact of the recent CRA regulation on bank ratings and hence their influence on banks' behaviour, are ongoing discussions among regulators, market participants and academics. Ensuring financial stability is a vital topic, given banks' crucial influence on the real economy, hence the debates on the design of regulatory regimes are not yet settled.[155] This Chapter contributes to understanding of the impact of regulation upon bank's decision-making and the consequences for the real economy.

This Chapter estimates a Discrete Choice Dynamic Programming (DCDP) model of bank behaviour. To the best of my knowledge, this is the first study to apply this methodology to bank decision-making (see Section 2.5.3). DCDP is a type of dynamic structural estimation that allows the explicit incorporation of a theoretical model into an empirical analysis. Rather than showing only that a relationship exists, DCDP reveals the mechanism behind the relationship (Low and Meghir, 2017). Moreover, once the model is successfully estimated, it can be used to postulate counterfactual policy scenarios and to evaluate their impact quantitatively and qualitatively. The Chapter applies the model in the presence of several frictions, whereby banks are rational, forward looking agents that must make a sequence of dynamic decisions to maximise their current and discounted future return on equity. Banks must decide on whether to (i) vary the extent of debt financing, (ii) adjust their business activities towards lending or non-interest income, (iii) solicit a credit rating. The model is estimated using the simulated method of moments (SMM), similar to Hennessy and Whited (2005).[156]

The Chapter employs annual bank level data for 6,121 banks from 27 European countries for the period 2004-2015. This data is used to build and estimate the model, ensuring that 100 different moments are matched (see Section 5.5.3), including a wide range of time-varying bank characteristics during pre-crisis, peak-crisis and post-crisis episodes in the sample period. The Chapter principally ensures that the simulated bank data, generated by the model, matches the actual average and standard deviations of various measurements of banks' behaviour and performance. The model replicates key mechanisms and feedback loops in the data, e.g. the ability for a bank's decisions to impact its credit rating, which in turn can impact the bank's cost of debt and hence its profitability. Once the simulated data from the model is consistent with the actual data, it becomes possible to run counterfactual scenarios, which involves

[155] In the US, for example, the debate over whether to repeal the bail-in regime for large bank holding companies continues (e.g. Berger et al., 2018).

[156] Hennessy and Whited (2005) explain that the advantage of SMM over IV and OLS regressions is that it does not suffer from simultaneity problems because it does not require any of the zero-correlation restrictions that are needed by the latter methods.

changing the underlying parameters and examining their impact on bank performance and behaviour.

Firstly, the Chapter examines what would have been the impact of the increased cost of insolvency caused by the European bail-in regulation, had it been implemented prior to the crisis in 2005. There is strong evidence that the bail-in regime may affect lending in the real economy. The model predicts the adoption of higher optimal capital ratios (consistent with Berger et al. (2018) and Leanza (2018)), driven by reduced debt levels, leading to a fall in bank insolvency rates during crisis periods (consistent with Dam and Koetter (2012)). However, this comes at the cost of a slight reduction in long term profits and banks shifting away from lending.

Secondly, the potential outcomes if the Basel III capital requirements (of 4.5% and 7% ratios) had been in place since 2005 are investigated. The simulations show a larger increase in bank capital and a larger decrease in bank debt (2 to 5 times greater) than that stimulated by the bail-in regime. Stronger bank stability during the financial crisis is revealed, with a lower number of insolvent banks. Banks seek alternative ways to maintain their profitability, given that their leverage has been constrained, which has a crucial impact on lending activity in the real economy.

Thirdly, the impact of CRA reforms are considered and the Chapter shows that banks react to changes in CRA rating practices via their actions in the debt/deposit market, adding to uncertainty in banks' lending activity. An increase (decrease) in CRA conservatism is associated with an increase (decrease) in a bank's cost of debt and a fall (increase) in the proportion of banks that choose to solicit a rating. More lenient ratings can directly result in increased rates of bank insolvency.

Lastly, the impact of changing market sensitivity to credit ratings is examined (see Section 5.6.4). The results indicate that increased (decreased) market sensitivity directly increases (decreases) bank's cost of debt. Bank's respond by reducing lending and being more circumspect when soliciting a rating. Additionally, the increased (decreased) sensitivity causes changes in the EU sovereign ratings to have a correspondingly greater (lesser) impact on bank's behaviour, by stimulating a greater (lesser) effort to manipulate their rating.[157]

[157] The recent EU sovereign debt crisis caused the fall of many banks' ratings due to the spill over of sovereign risk through the sovereign-bank rating channel (Alsakka et al., 2014).

The results underline the importance of understanding the mechanisms through which regulation can impact bank decision-making behaviour and performance. By building and estimating a dynamic model with actual data, it is possible to replicate the various relationships at play, investigate the underlying mechanisms, and eliminate endogeneity issues. It allows us to observe not only the direct impact of the regulation (e.g. capital ratios or bail-in policy), but also how this can have knock-on implications to other less anticipated aspects of bank behaviour and be able to form an accurate prediction of the policy changes. This provides a strong framework to consider the real effects of bank decision-making in the economy.

The remainder of the Chapter is organised as follows. Section 5.2 reviews related prior studies, while Section 5.3 describes the data sample and the results of a set of regressions highlighting key dynamic relationships in the data. Section 5.4 outlines the full empirical model, and Section 5.5 discusses the estimation approach and parameter estimates. Section 5.6 presents the counterfactual scenarios involving regulatory changes, and Section 5.7 concludes.

5.2 LITERATURE REVIEW

Theoretical and empirical research on dynamic corporate finance has grown dramatically over the past 25 years (see Strebulaev and Whited, 2011) and a body of literature has developed that utilises dynamic models to examine firm financing. Gomes (2001) builds and calibrates a dynamic model of firm financing and investment decisions, including investment and financing costs. Cooley and Quadrini (2001) builds and calibrate a dynamic model of firm financing with financial market friction, industry dynamics and persistent shocks. Cooper and Ejarque (2003) are the first in this strand of the literature to estimate a dynamic model,[158] where imperfectly competitive firms face financial constraints and use market power to induce the principal link between investment and internal funds. Hennessy and Whited (2005) examine firm leverage utilising a dynamic trade-off model with corporate income tax, financial distress costs, endogenous choice of leverage and equity flotation costs, and then utilise SMM to estimate the model using actual data. Specifically, they solve the model via value function iteration and use the solution to generate a simulated panel of firms. Hennessy and Whited (2007) then extend their previous dynamic model of firm financing to examine the magnitude of financing costs (cost of debt) for corporations. Another paper that extends Hennessy and Whited (2005)'s model is Gamba and Triantis (2008) who separately control for the borrowing and lending decisions of the firm, introduce an issuance cost for debt and allow capital to be sold at a discount.

A separate strand of literature focuses on the recent regulatory changes in response to the 2008 financial crisis, in particular bail-in mechanisms and capital requirements reforms. The potential for a bail-in resolution shifts the burden of losses from the government to equity and debt holders first (Conlon and Cotter, 2014). The increased burden on these stakeholders could reduce bank risk taking, e.g. Hilscher and Raviv (2014) show that a bail-in regime could be an effective tool for stabilizing financial institutions. However, DeYoung et al. (2013) find that increased government intervention can make banks more risk insensitive and increases insolvency risks. Attaoui and Poncet (2015) report that firms' total market values are larger in the presence of write-down debt, such as the bail-in requirement. Berger et al. (2018) examine the impact of US regulatory efforts on bail-in by developing and testing a dynamic model of optimal regulatory design that examines three scenarios of bailout, bail-in and no regulatory

[158] They follow the procedure in Gouriéroux and Monfort (1996).

intervention. They conclude that regulatory intervention is always optimal and that only the bail-in provides incentives for banks to build up capital reserves pre-emptively during distress.

The literature on banks' capital requirements (see Section 2.4.1) shows that well capitalised banks have improved performance and lead to lower insolvency rates (Berger and Bouwman, 2013; Miles et al., 2012). Bhagat and Bolton (2014) and Miles et al. (2012) also argue that banks should be financed with considerably more equity than the historical norms. There is also much debate over how capital requirements should be constructed (Cuoco and Liu, 2006; Blum, 2008; Admati and Hellwig, 2013; Benhabib et al., 2016). The discussion is on what level of capital should be required and whether it should be flat or counter-cyclical.

There is sparse literature on the recent regulatory reforms of CRAs (see Section 2.3.4). Bannier et al. (2010) show that ratings which expose a CRA to greater scrutiny tend to be downward biased (more conservative) and that the effect is stronger for more opaque industries (such as banking), yet they do not explore the impact of the regulation. Their logic is extended, and it is argued that increased oversight of CRAs will strengthen this downward rating bias. Hence, an increase in conservatism is likely to result in lower bank ratings. This will influence bank behaviour, because ratings are a strong determinant of the cost of debt. Evidence from the US corporate rating market (Dimitrov et al., 2015) has shown a fall in rating levels accompanied with a reduction in market reactions (sensitivity) to rating downgrades.

While the literature includes many models of banking behaviour (e.g. Calem and Rob, 1999; De Nicolo et al., 2014; DeYoung et al., 2015; Valencia, 2014a; Heuvel, 2008; Peura et al., 2006; Repullo, 2004; see Section 2.5.2), they are either static, purely theoretical or produce calibrations. DeYoung et al. (2015) estimate a static structural model of bank portfolio lending and show that US community banks reduced their business lending during the global financial crisis. Repullo (2004) builds a theoretical model of imperfect competition in banking where banks can invest in a prudent or a gambling asset under either a flat-rate capital requirement or deposit rate ceilings. De Nicolo et al. (2014) and Calem and Rob (1999) calibrate dynamic models of banking; the former study examines the impact of micro prudential bank regulations on bank lending, while the latter creates a dynamic portfolio choice problem facing banks. Valencia (2014a) develops and calibrates a bank model to study supply-driven contractions in credit, where banks are affected by financial frictions when raising external funds. Heuvel (2008) dynamically models banks to examine the welfare cost of bank capital requirements. Peura et al. (2006) calibrate a dynamic model of banks to study bank capital choice as a dynamic trade-off between the opportunity cost of equity and loss of franchise value after falling below the regulatory capital requirement and needing to recapitalize. To the best of my knowledge, while there are many dynamic theoretical and calibrated models of banking, no study estimates a dynamic model of banking. This is surprising, given the success of dynamic structural estimation in other areas of corporate finance.

Calibration involves the matching of a small number of moments and does not provide any information about the confidence in the results. Dynamic structural estimation is performed on several moments (100 in this Chapter) and provides standard errors (usually using Simulated Maximum Likelihood (SML) or Simulated Methods of Moments (SMM)). One approach for creating and estimating dynamic models is the use of DCDP. The DCDP methodology has predominantly been applied in the field of labour economics (see Section 2.5.3), starting with the seminal work by Keane and Wolpin (1994). It involves the solving of the expected maximum utility (*Emax)* function at every point in the state space (see Section 5.5.1). Following the calculation of every possible future path, the model then is forward simulated whereby agents can base their choices on their expected future utility. A simulated panel dataset is then obtained which can then be compared to the actual panel data set, where convergence between the simulated and actual data sets may be achieved through the adjustment of parameters. The use of DCDP has seen much success in examining such topics as volunteering (Sauer, 2015), labour markets (Keane and Wolpin, 2010; Keane and Sauer, 2009; Sauer, 1998) and the link between race and attainment (Keane and Wolpin, 2000).

The Chapter's research question is linked to a range of existing literature and it applies an innovative methodology to the field, consequently being able to develop new insights into banks' behaviour. To the best of my knowledge, there is no prior literature that estimates a dynamic model of banks. Finally, there is also no consensus on the impact of new regulatory reforms on banking behaviour in the real econmy and this Chapter aims to shed light as to the nature of these reforms.

5.3 DATA DESCRIPTION AND ILLUSTRATIVE ANALYSIS

The sample initially includes 6,121 banks from 27 EU countries during the period 2004 to 2015 (see Table 5.1), as this period encapsulates both the run up to, and subsequent recovery from, the financial crisis of 2008 and incorporating more years would mean a substantial increase in computational time. The variables' definitions and data sources are reported in Panel A of Table 5.2. Similar to Hennessy and Whited (2005), banks with total assets of less than two million Euros and equity less than one million Euros are not included. Observations that fail to obey standard accounting identities are excluded. Annual bank observations that have more than three of the following variables missing are also omitted: equity, debt, gross loans to total assets, cost of debt, return on loans, return on non-interest activities, interest rate and sovereign rating.[159] The resulting dataset is an unbalanced panel of banks with between 1,454 and 2,824 observations per year, and a total of 30,631 bank-year observations.[160] The summary statistics for the EU sample are displayed in Table 5.3 and the distribution of key variables is shown in

Figure A. 5.1.

Bank credit ratings' dataset is gathered from the BankScope database and includes ratings by S&P, Moody's and Fitch. The credit ratings are mapped to an 18-notch rating scale: AAA/Aaa = 18, AA+/Aa1 = 17, AA/Aa2 = 16 …, CCC+/Caa1, CCC/Caa2, CCC-/Caa3 = 2, C/SD/CC/D = 1 (shown in Table 5.4).[161] If the banks are rated by multiple CRAs then the ratings are averaged and rounded to the nearest whole number (category).

5.3.1 ILLUSTRATIVE ANALYSIS

The process of modelling bank behaviour is guided by the dynamics in the data as well as theories from previous literature. As a precursor to specifying a theoretical model, a preliminary analysis is conducted. This involves a series of OLS and ordered logit regressions (presented in Panel B of Table 5.2 and discussed further in Section 5.4) that enable us to explore the relationship between various components in the dynamic model. The variables are all

[159] To eliminate outliers, the top and bottom 2% is trimmed off all the variables, except return on loans, return on non-interest activities and gross loans to total earning assets, for which 3% is trimmed off the top.
[160] The data is adjusted to 2015 prices using a GDP inflator from the World Bank and OECD national accounts data.
[161] Unlike S&P and Moody's, Fitch does not differentiate between ratings at the CCC/Caa level since 2006.

defined in in Panel A of Table 5.2. This is a standard approach in the literature on dynamic structural estimation (see Keane and Wolpin, 2009).

5.3.1.1 Return on loans, return on non-interest activities and credit ratings

The first set of estimated regressions investigates the return generated from bank loans, which is calculated following Kwast (1989):

$$X_{i,t} = \frac{Total\ interest\ income}{Gross\ Loans} = 2\frac{TII_{i,t}}{\left(GL_{i,t} + GL_{i,t-1}\right)} \tag{5.1}$$

The results reported in Panel A of Table 5.2 suggest that: (i) loan rates are higher during and following the financial crisis, (ii) loan rates are positively associated with interest rates and (iii) banks located in countries with high sovereign credit rating levels tend to have higher returns on loans.

Secondly, the determinants of non-interest activities income are considered. The return on non-interest activities (Y) in the sample is calculated following Kwast (1989),[162] whereby the total non-interest income is used:

$$Y_{i,t} = \frac{Total\ non\ interest\ income}{TA - Gross\ Loans} = 2\frac{TNII_{i,t}}{\left(\left(TA_{i,t} + TA_{i,t-1}\right) - \left(GL_{i,t} + GL_{i,t-1}\right)\right)} \tag{5.2}$$

The results from the regressions reported in Panel B of Table 5.5 reveal that: (i) banks in countries with stronger economic conditions generate more non-interest income and (ii) non-interest income fell during the financial crisis.

The third set of estimated regressions explores the variables associated with banks' credit ratings. The results reported in Panel C of Table 5.5 suggest that (i) credit ratings are 'sticky', i.e. depend upon their past values; (ii) bank credit ratings are lower during crisis periods; (iii) banks located in countries with higher sovereign credit ratings tend to have higher credit ratings, consistent with a sovereign-bank rating ceiling (e.g. Almeida et al., 2017); (iv) traditional banks tend to have lower credit ratings than fee-based banks.

---

[162] Non-interest activities are defined here as business activities which do not involve lending. In Section 5.4, when considering bank business models, the focus is on the ratio of Gross Loans to Total Earning Assets as a more direct lending-related measure. The assumption of categorizing bank assets into two different types (often termed safe and risky) is consistent with earlier research (e.g. Gennaioli et al., 2013; Hanson et al., 2015).

5.3.1.2 Equity, dividends and share capital

The change in equity is modelled using a method commonly applied in the literature (e.g. Peura and Keppo, 2004).[163] The results are presented in Panel A of Table 5.6 and confirm that equity increases with positive net income and injections of share capital, and equity falls when issuing dividends. Next, bank dividend payments are analysed (Panel B of Table 5.6) and it is found that: (i) companies with more equity tend to issue more dividends and (ii) banks tend to issue more dividends in profitable years. Larger companies issue more share capital, consistent with expectations (Panel C of Table 5.6).

5.3.1.3 Banks' expenses, corporation tax and cost of debt

Next banks' operating expenses and the cost of debt is considered. In this Chapter, 'debt' includes both debt and deposits. As expected, it is shown that banks' operating expenses do indeed scale with firm size (Panel A of Table 5.7). In addition, a t-test is performed (see Table A. 5.1) examining whether banks that changed their debt or business model incurred higher expenses (consistent with adjustment costs in the literature (e.g. Gomes, 2001; Hennessy and Whited, 2005, 2007). The results in Panel B of Table 5.7 show that banks that decide to greatly change their debt (large increase or decrease) incur additional expenses (1.154% increase in expenses as a percentage of total assets). There is also an increase in expenses (0.231%) associated with a 1% shift in the bank's business model, either a shift to more lending activities or a shift to more non-interest activities. Following De Nicolò et al. (2014) and Hennessy and Whited (2005), corporation tax is included in the model. However, the tax rate varies across countries and years, therefore the weighted average corporation tax for banks in the sample is employed and found to be 28.86% (using 30,508 observations).

For the cost of debt, the results reported in Panel C of Table 5.7 reveal that (i) the cost of debt increases with interest rates (consistent with a standard model of loans); (ii) the cost of debt increases during crisis periods (as funding is scarcer and drives up the cost of debt); (iii) higher rated companies experience a lower cost of debt (consistent with the literature on debt markets);

---

[163] The literature typically models the change in equity as $Equity_t = Equity_{t-1} + Net\ income_t - Dividends_t + Change\ in\ share\ capital_t$. Although individual models vary as to whether they include estimates for the dividends paid and the change in share capital, Peura and Keppo's (2004) model is applied as it is the most appropriate in the setting.

(iv) more highly leveraged banks (increased credit risk) incur increased costs of borrowing; and (v) loan-focused banks incur higher costs of borrowing compared to trading or fee focused institutions. Additionally, a t-test confirms that larger banks use more long-term debt (see Table A. 5.2), this supports the trend observed in Figure A. 5.2. Long term debt is typically issued in the form of bonds and requires access to capital markets, which in turn necessitates a credit rating. Use of capital markets without a credit rating will require companies to pay a higher return on the debt to attract investors. Hence, unrated banks that use more long-term debt (typically larger banks), will see an increase to their cost of debt. A term is included to account for the additional cost of debt incurred by being a large unrated bank (see Section 5.4.2).

5.4 THEORETICAL MODEL

This Section outlines the components of the DCDP model of bank behaviour. Bank behaviour is simulated from 2005 until 2015. Bank i maximises its present and future profitability (ROE) in period t. Each bank raises funds and then engages in some proportion of lending and non-interest activities. Choices are made by banks at the beginning of the period prior to the realization of the time variant shocks. This follows the standard approach in the literature (Bakke and Gu, 2017; Calem and Rob, 1999; DeAngelo et al., 2011; De Nicolò et al., 2014; Hennessy and Whited, 2005).

The first choice a bank makes in each period is whether to increase or decrease the amount of debt, denoted as $\widetilde{D}_t \in \{-2,-1,0,1,2\}$. The benefit of greater leverage is the increased resources available to invest in assets, and therefore a bank may achieve a higher ROE. However, higher leverage increases the risk of financial distress, especially during times of high loan failure e.g. a financial crisis. It also has an adverse impact on its credit rating and hence cost of debt. Moreover, having lower levels of debt may reduce the risk of insolvency, and can lead to a higher credit rating and lower cost of debt. The second choice a bank makes in each period is whether to vary the type of business it conducts, deciding between loans and non-interest activities to maximise its ROE. This decision is denoted by $\tilde{\lambda}_t \in \{-2,-1,0,1,2\}$. Shifting to increasingly non-interest activities may pay off in the current period but could impact a bank's credit rating and cost of debt in the future. The third choice a bank makes in each period is whether to solicit a rating from a CRA, with $CR_t \in \{0,1\}$. A bank may solicit a rating from a CRA for two reasons: enabling access to capital markets and lowering the cost of debt.

Therefore, in each period, the bank will select one of the 45 possible choices.[164] Any profit or loss is carried over to the following period, impacting the bank's equity. The model also includes costly debt (*D*), corporation taxes (τ), dividends (*Div*), share capital (*SC*) and expenses. It contains four potential shocks, one each on X_t and Y_t returns, on expenses and on the credit rating, (see Eqs. (5.1) and (5.2)).

ROE is a common metric for bank success and influences managerial remuneration (Doucouliagos et al., 2007). Therefore, banks maximise:

[164] There is a restriction of choosing the largest debt increase (debt choice = 2) to rated institutions only (see Section 5.4.6), hence there are 45 not 50 possible choices. Consequently, there are 45^{15} possible decision paths.

$$\max_{d_t}\left\{ROE_{d_t}(I_t) + E\left[\sum_{k=t+1}^{T} \delta^{k-t} ROE_{d_t}(I_t)|I_t, d_t\right]\right\} \tag{5.3}$$

Profits are comprised of the *ROE* at time *t* plus the discounted stream of expected future ROE from all future periods (*k* to *T*) associated with decisions d_t. In Eq. (5.3), δ is the discount rate,[165] I_t is the array of states. Following Keeley and Furlong (1990), profits are defined as:

$$ROE_{i,t} = \frac{[TI_{i,t} - TE_{i,t}] \times (1-\tau)}{Eq_{i,t-1}} \tag{5.4}$$

Where τ represents the tax rate, which is assumed constant over the time period, $TI_{i,t}$ is the total income, $TE_{i,t}$ is the total expenses and $Eq_{i,t-1}$ is the equity at the start of the period.

The bank's income derives from loans and non-interest activities. $X_{i,t}$ and $\sigma_{x,i,t}$, represent the mean and standard deviation of the return on loans, while $Y_{i,t}$ and $\sigma_{y,i,t}$ are the mean and standard deviation of the return on non-interest income activities, where $\sigma_y > \sigma_x$. The proportion of gross lending to total earning assets (GL-TEA) is given by $\lambda_{i,t}$. The distribution of assets is then scaled up by the total assets $TA_{i,t}$, which is given by the sum of equity $Eq_{i,t}$ and debt (including both debt and deposits) $D_{i,t}$.

$$\begin{aligned} TI_{i,t} &= \left(X_{i,t}\lambda_{i,t} + Y_{i,t}(1-\lambda_{i,t})\right) * TA_{i,t} \\ &= \left(X_{i,t}\lambda_{i,t} + Y_{i,t}(1-\lambda_{i,t})\right) * \left(Eq_{i,t} + D_{i,t}\right) \end{aligned} \tag{5.5}$$

$TI_{i,t}$ is the overall income from the combination of earning assets stated as follows (adapted from Kwast's (1989) definition[166]). The business model, $\lambda_{i,t}$, (GL-TEA) will change as follows:

$$\lambda_{i,t} = \lambda_{i,t-1} + \beta_{\lambda,1}(\tilde{\lambda}_{i,t}) \tag{5.6}$$

Therefore, the banks' business comprises: (i) traditional lending activities, and (ii) non-interest activities, which include securities and investment banking (e.g. Abedifar et al., 2018). If the bank is mainly engaged in traditional lending activities, λ will be relatively high.

[165] The discount factor (δ) is set at 0.95 (e.g. De Nicolo et al., 2014).

[166] $E(R) = \lambda E(RS) + (1-\lambda)E(RNS)$, where RS is return on securities activities and RNS is return on non-securities activities.

The bank incurs two types of expenses: (i) financing costs (as in Gomes, 2001), where the cost of debt depends on macro-economic conditions (interest rate, sovereign rating), bank credit rating and bank size (see Section 5.4.2) and (ii) operating expenses (*EXPS*). These operating expenses scale with firm size and include adjustment costs (as in Gomes, 2001; Hennessy and Whited, 2005, 2007) associated with changing the proportion of debt financing and the business model (see Section 5.4.3). The resultant equation follows:

$$TE_{i,t} = COD_{i,t} * D_{i,t} + EXPS_{i,t} * TA_{i,t} \tag{5.7}$$

A bank's debt will change as follows:

$$D_{i,t} = D_{i,t-1}(1 - D\_decay) * \left[1 + \beta_{D,1}\left(\widetilde{D}_{i,t}\right)\right] \tag{5.8}$$

Where $D_{i,t-1}$ is the debt at time *t-1*, *D_decay* is the annual proportion of debt that matures and $\widetilde{D}_{i,t}$ is the bank's choice about the new amount of debt. This Chapter follows a standard assumption in the literature that debt decays over time, due to loans (debt) reaching maturity. Following the technique used by De Nicolò et al. (2014) and Hennessy and Whited (2005), the decay of debt is modelled over time.

5.4.1 RETURN ON ASSETS

The assumption of categorizing bank assets into two different types (often termed safe and risky) is consistent with some earlier literature (e.g. Benhabib at al., 2016; Gennaioli et al., 2013; Hanson et al., 2015). First, the Chapter models the return on loans assuming (as in DeYoung et al., 2015) that the probability of loan defaults depends on the economic conditions, both in the wider (European) economy and in the regional (country) economy and as such is modelled as:

$$X_{i,t} = \beta_{X,0} + \beta_{X,1}\left(\frac{Ec_{i,t} + Ec_{i,t-1} + Ec_{i,t-2}}{3}\right) + \beta_{X,2}IR_{i,t} + \beta_{X,3}SR_{i,t} + \varepsilon_{X,1} \tag{5.9}$$

Where *Ec* is a measure of the financial crisis (using the VSTOXX European market volatility index and is exogenous) and captures the wider economic uncertainty. A 3-year moving average is applied to reflect past economic conditions affecting the current loan default rate. Interest rates (*IR*) change as follows:

$$IR_{i,t} = IR_{i,t-1} + \beta_{IR}\varepsilon_{SR,1} + \varepsilon_{IR,1} \quad (5.10)$$

Sovereign rating (*SR*) captures the country economic conditions. Countries with low sovereign credit rating have a much higher country risk factor and a correspondingly higher loan default rate. The sovereign rating changes as follows:

$$SR_{i,t} = SR_{i,t-1} + \varepsilon_{SR,1} \quad (5.11)$$

This study follows Gennaioli at al. (2013) and Hanson et al. (2015) in modelling the return of non-interest activities as a function of economic conditions. Three categories of economic conditions: good state (growth), bad state (down-turn) and recession are employed. The return from non-interest activities is therefore modelled as follows:

$$Y_{i,t} = \beta_{Y,0} + \beta_{Y,1}SR_{i,t} + \beta_{Y,2}Ec_{i,t} + \varepsilon_{Y,2} \quad (5.12)$$

5.4.2 COST OF DEBT

This is modelled in two parts, based on existing debt (Ω) and new debt to taken on during this period (ω).[167] The overall cost of debt will therefore depend on both the existing debt and the new debt:

$$COD_{i,t} = (1-\theta_t) * COD_{i,t}(\Omega) + \theta_t * COD_{i,t}(\omega) \quad (5.13)$$

Where θ is the proportion of new debt. The cost of existing debt depends most significantly on current interest rates and the wider economic environment (as this will determine the availability of funds and hence the price) and will therefore be modelled as:

$$COD_{i,t}(\Omega) = \beta_{COD,0} + \beta_{COD,1}IR_{i,t} + \beta_{COD,2}Ec_{i,t} \quad (5.14)$$

Increased interest rates (IR_t) raise the cost of borrowing for all market participants. This hypothesis is supported by Merton (1974) who states that the cost of a firm's debt will depend on the interest rate and the volatility of the firm's values (or its business risk) as measured by the variance. Moreover, the firm's business risk will vary with the economic conditions (Ec_t).

[167] Due to computational limitations, it is not possible to keep track of each past period's cost of debt.

A bank's cost of newly added debt will impact the bank's decisions regarding whether to solicit a credit rating and to issue new debt. Depending on whether the bank is rated or not, different factors are considered when estimating the cost of new debt issuance. For a rated bank, the cost of issuing new debt is modelled as:

$$COD_{i,t}(\omega) = COD_{i,t}(\Omega) + \left[\beta_{COD,3} + \beta_{COD,4}e^{\beta_{COD,5}CR_{i,t}}\right] + \beta_{COD,6}\left(\frac{TA_{i,t}}{Eq_{i,t}}\right) + \beta_{COD,7}\lambda_{i,t} + \beta_{CRA\ Fee} \qquad (5.15)$$

$\beta_{COD,3} + \beta_{COD,4}e^{\beta_{COD,5}CR_{i,t}}$ capture the impact of the credit rating on the cost of debt, which can be positive or negative.[168] Credit ratings are a key determinant of the cost of a firm's debt in capital markets (e.g. Almeida et al., 2017).[169] In addition to a bank's credit rating, investors consider other key risk indicators including the bank's leverage (Berger and Bouwman, 2013) and its type (Altunbas at al., 2017) when evaluating credit risk. The CRA fee is also included and is set as 0.0675% of the size of the issue.[170] The regression results support the above relationship (see Section 5.3.1.3).

For unrated banks, the cost of debt for newly issued debt is modelled as:

$$COD_{i,t}(\omega) = COD_{i,t}(\Omega) + \beta_{COD,8} + \beta_{COD,6}\left(\frac{TA_{i,t}}{Eq_{i,t}}\right) + \beta_{COD,7}\lambda_{i,t} + \beta_{COD,9}TA_{i,t} + \beta_{COD,10}SR_{i,t} \qquad (5.16)$$

For unrated banks, the first two additional terms ($\beta_{COD,3} + \beta_{COD,4}e^{\beta_{COD,5}CR_{i,t}}$) are omitted and replace them with $\beta_{COD,8}$ which is a constant. The additional term $\beta_{COD,9}TA_{i,t}$ is included to capture the additional cost to larger banks of being unrated. This arises because larger firms typically use more long-term debt (Custódio et al., 2013). Large debt issuance without a credit rating is highly unusual, as it would require the institution to offer a significant premium on their debt to attract investors.[171] This term represents that premium and the value is fixed from

[168] The constant $\beta_{COD,4}$ and the exponential constant $\beta_{COD,5}$ are fixed from the data and are not changed during the estimation. The scaling constant $\beta_{COD,3}$ is estimated.

[169] Elton et al. (2001) shows that bonds from financial sector companies with lower ratings have significantly higher rates (than highly rated FIs) and therefore those companies have significantly higher cost of debt. Elton et al. (2001) show that the spread from treasury bonds is roughly twice as large for financial sector corporations rated BBB as for those rated AA (on bonds with a maturity of less than 10 years).

[170] S&P's fee for corporates.

[171] It is so unusual that the model restricts the choice to solicit a large amount of debt without a credit rating.

the data. As no credit rating is present, bond investors will also consider the financial state of the host country when evaluating the credit risk. The additional term $\beta_{COD,10}\, SR_{i,t}$ are included to account for the country level risk factor.

5.4.3 EXPENSES AND TAXATION

Bank expenses are modelled as a function of size and adjustment costs. Firstly, it is assumed that expenses will scale with size (see Section 5.3.1.3). The Chapter also follows a standard assumption in the literature (Gomes, 2001; Hennessy and Whited, 2005, 2007) whereby businesses incur *adjustment costs*. There are two types of adjustment cost usually employed, either *fixed* or *convex* (Strebulaev and Whited, 2011). This study opts for *convex* adjustment costs as they better capture the size of the change. The adjustment costs apply to both a change in the debt level and a change in the business model. Debt adjustment costs arise from the costs associated with accessing capital markets and of issuing short term/long term debt.[172] Equally, there are costs associated with shifting the banking business from lending to more non-interest focused business or vice versa.[173]

$$EXPS_{i,t} = \left(\beta_{Ex,0} + \beta_{Ex,1}\left[\beta_{D,1}\left(\widetilde{D}_{i,t}\right)\right]^2 + \beta_{Ex,2}\left[\beta_{\lambda,1}\left(\tilde{\lambda}_{i,t}\right)\right]^2 + \varepsilon_3\right) * \left(Equity_{i,t-1} + Debt_{i,t}\right) \tag{5.17}$$

Further, the Chapter includes a corporation tax of 28.86% (see Section 5.3.1.3), close to the value used by Hennessy and Whited (2005) (of 30%).

5.4.4 EQUITY, DIVIDENDS, AND SHARE CAPITAL

The bank's equity can change over time, as in De Nicolò et al. (2014) and Peura and Keppo (2004). Equity is more expensive than debt (e.g. DeYoung et al., 2015)[174] and Hennessy and Whited (2005) show that it is generally optimal to leave debt outstanding than to replace with equity. Therefore, in the model, if banks wish to raise additional capital, they can choose to

[172] A t-test confirms that banks that make large changes to their debt level have significantly higher expenses as a proportion of their total assets (see Table A. 5.1).
[173] An additional t-test confirms that banks that make a large shift towards lending activity (or towards non-interest activities) have much higher expenses than those that make no change to their business model (see Table A. 5.1).
[174] Specifically, that the opportunity cost of capital is larger than the interest rate on deposits.

raise debt. Further, banks pay dividends to shareholders, and the average dividend payout each period is matched, dependent on bank size and net income. Banks also receive a small amount of share capital, which depends on the size of the bank.[175]

Consistent with the literature, banks retain earnings which are then reinvested with a view to increasing the value of equity (e.g. De Nicolò at al., 2014; Repullo, 2004). The next period's equity level is modelled as:

$$Eq_{i,t} = Eq_{i,t-1} + NI_{i,t} - \beta_{Eq,1} Div_{i,t} + \beta_{Eq,2} SC_{i,t} \tag{5.18}$$

Where $Div_{i,t}$ is the dividend issued by the bank and $SC_{i,t}$ is the change in share capital. This relationship is shown to hold in the data (see Section 5.3.1.2). The Chapter also includes the total dividends. A simple estimation of the average dividend paid each year is included, based on the size of the bank's equity and the net income generated that year.

$$Div_{i,t} = \beta_1 Eq_{i,t-1} + \beta_2 NI_{i,t} \tag{5.19}$$

Higher profits lead to the firm being able to pay (or pay a larger) dividend that period and as such β_2 is positive. This positive relationship between revenue and dividends is shown by Dickens at al. (2002) and others. The relationship in the above equation is fully supported by the data (see Section 5.3.1.2). Due to limitations in computational power, share capital cannot be specified here as a choice variable, so the average amount of share capital of each institution is estimated based on their characteristics and this is then matched to the actual data. The trend shown in the data is that larger banks issue more share capital at each offering. The relationship is modelled as:

$$SC_{i,t} = \beta_1 TA_{i,t} = \beta_1 \left(Eq_{i,t-1} + D_{i,t} \right) \tag{5.20}$$

5.4.5 BANK CREDIT RATINGS

A bank's credit rating is a metric that captures the probability that the bank will be unable to repay its debts. They are used in a variety of areas, from determining bond spreads in capital

[175] Because equity is more expensive than debt, should a bank wish to raise more funds, it is assumed this would be done via raising debt. Therefore, the model does not include the change in share capital as a choice variable. However, since share capital does change over time, it is chosen to model the overall average change each period based on a bank's size.

markets to being relied upon by government regulation. As such, a bank's credit rating can have a wide-ranging impact upon its activities. The greatest impact is on the bank's cost and availability of debt. Banks require a credit rating to access capital markets and to be able to issue bonds in a cost-effective manner. A poor rating can limit the potential investors in a bank's debt and require the bank to offer a premium to attract more risk-tolerant investors. Many studies show how a credit rating significantly impacts the cost of debt (e.g. Almeida et al., 2017; Elton et al., 2001; Nozawa, 2017).

It is necessary to consider the various factors that affect the rating that a bank will be assigned. Leverage captures the capital structure and is a strong determinant of bank risk (Berger and Bouwman, 2013). White and Cole (2012), and others, find that higher capital levels improve banks' performance during the financial crisis. This is captured in the same manner as Hau at al. (2013) by using the ratio of total assets to equity. Bank business model is also known to have an impact on the risk of the bank (Altunbas at al., 2017). Moreover, the rating is highly dependent on its past value and the financial crisis (market volatility, captured by VSTOXX). Finally, risk can be transferred from sovereigns to banks through a rating channel (e.g. Almeida et al., 2017) and normally acts as an upper bound to the rating level. It is then necessary to include the sovereign rating of the bank's host country to capture any such transmission of risk. A bank's credit rating is therefore modelled as:

$$\begin{aligned} CR_{i,t} = {} & \beta_{CR,0}(1 - Rated_{i,t-1}) + \beta_{CR,1}CR_{i,t-1}Rated_{i,t-1} + \beta_{CR,2}Ec_{i,t} + \beta_{CR,3}SR_{i,t} \\ & + \beta_{CR,4}\lambda_{i,t} + \beta_{CR,5}\left(\frac{TA_{i,t}}{Eq_{i,t-1}}\right)^2 + \varepsilon_{CR,1} \end{aligned} \tag{5.21}$$

Where $Rated_{i,t-1}$ is a dummy variable equal to 1 if the bank was rated in the previous period. $\varepsilon_{CR,1}$ is a shock, that captures the uncertainty facing banks when predicting their ratings.

5.4.6 CONSTRAINTS

Banks are subjected to a regulatory minimum capital ratio, which is the minimum ratio of equity to total assets:

$$\frac{Eq_{i,t}}{TA_{i,t}} \geq \min\left(\frac{Eq}{TA}\right) \qquad (5.22)$$

During the sample period, two sets of capital requirements prevailed in Europe. First, Basel II brought in an initial common equity tier 1 capital ratio of 2% in 2006.[176] Second, the equity tier 1 capital ratio was extended by the Basel III regime to 4.5% in 2013.[177]

Moreover, if a bank wishes to raise a large amount of debt, accessing capital markets is the only realistic way to raise the funds. To access these capital markets, the bank must require a credit rating, as the vast majority of bonds are rated (e.g. Edwards at al., 2007).[178] Therefore the model restricts the choice of the largest debt increase (debt choice = 2) so that it is only available to rated institutions.

[176] EU Directive 2006/49/EC of 14th June 2006.

[177] EU No 575/2013 Article 92 of 26th June 2013.

[178] Edwards at al. (2007) find that only 0.5% of the total value of corporate bonds traded are unrated.

5.5 RESULTS

5.5.1 EMPIRICAL STRATEGY

This Chapter employs the simulated method of moments (SMM) (McFadden, 1989; Pakes and Pollard, 1989) to estimate a DCDP model. To the best of my knowledge, it is the first time that a DCDP has been applied to model bank behaviour.[179] DCDP allows a theoretical model to be explicitly incorporated in the empirical analysis, and it relies on the discretization of the decision space. The main advantage of using a dynamic structural estimation approach is the discovery of the mechanism that produces observed outcomes (Low and Meghir, 2017). Rather than showing only that a relationship exists, DCDP can reveal the underlying mechanism for the relationship. Therefore, this approach allows one to move beyond the conclusions of a study that provides reduced-form causal relationships. Also, once the model is correctly estimated, it can be used to postulate counterfactual policy scenarios and evaluate their impact quantitatively and qualitatively. While the validation of the model is based on the chosen dataset, the implications are wider. However, the main disadvantage of a dynamic structural estimation approach is that it is computationally highly time consuming.

The first step is to formulate a dynamic model of optimal bank financing and investment policy when under several frictions, including: costly debt, corporate taxation, credit ratings, convex adjustment costs and bankruptcy costs. Bank managers attempt to maximise their return on equity (ROE) subject to the frictions and restrictions detailed in the model (see Section 5.4). The second step is to code the model in order to generate a simulated panel data set, whose moments can then be compared to the actual panel data. The third step consists of adjusting the parameters of the model one by one, until the distance between the two sets of moments is minimized, thereby yielding consistent estimates for the unknown parameters (as in Hennessy and Whited, 2005, 2007).

A full solution backwards recursion method is used to conduct the estimation. This involves first solving the model, for estimated parameters, by backwards recursion. To do this, the full numerical solution method is used where the expected maximum (*Emax)* function is solved at

[179] DCDP has been used extensively in labour economics, industrial organisation, and political economy among others (Keane and Wolpin, 2009).

every $t = 1, \ldots, T$, as pioneered by Keane and Wolpin (1994).[180] Following the calculation of every possible future path, the model is forward simulated to obtain the simulated panel data and lifecycle paths for 6,121 banks. Since the state space cannot be continuous, it is discretized with the following number of categories: Equity – 20, Debt – 20, Business Model – 10, Credit Rating – 19, Interest Rates – 5, Sovereign Rating – 4, Financial Crisis periods – 3 and Time – 15. The number of categories is big enough to guarantee enough heterogeneity in the results. Of course, adding more categories would increase the precision of the results, but it would also increase the computational time and space beyond what is currently feasible with personal computers.

5.5.2 IDENTIFICATION

Central to evaluating the model are the moments utilized. The larger the number of moments, the higher is the precision of the model. Matching only 5 or 10 moments (as is commonly observed with calibration) would be too few to achieve robust estimations. 100 moments are employed to match the model to actual data while estimating 40 parameters. This means that on average each parameter is identified by over two moments and therefore one can be confident that the simulated dataset is able to match the real data accurately.

The set of moments used in the estimation are chiefly dynamic and include choice dimensions, they are split into four groups. The first group contains moments that are linked to profitability (ROE, ROA) and income from banking activities (returns on loans and non-interest activities) and these are used to identify the parameters associated with loan income, non-interest activity income, the correlation between shocks affecting the two and dividends.

The second group contains moments that are used for examining bank behaviour. These include the time varying levels of bank's debt and equity, in addition to the average business model, ratio of equity to total assets over time, value of dividends paid, share capital issued by banks over time and the insolvency rates in each period. These moments enable identification of the importance of bank capital ratios, the unobservable cost of insolvency, the weight that CRAs place on various factors and the decision by a bank to solicit a rating.

[180] The *Emax* function is the expected utility, i.e. predicted ROE, associated with any given choice in any given circumstances (state space) for the bank. This means that the potential profit generated by any bank with any characteristics, making any choice, at any time ($t = 1,\ldots,T$) is calculated (3.078 billion possibilities). Using this array of values, a bank can model what choice now will best serve to maximise its current and future profits.

The third group of moments examines bank credit ratings, cost of debt and expenses. These moments identify the impact of sovereign ratings (through the sovereign-bank rating channel), economic uncertainty, bank business models and capital ratios on credit ratings assigned to banks. Additionally, they enable identification of the relationship between a bank's cost of debt and its rating and the impact that interest rates, economic uncertainty and capital ratios have on a bank's cost of debt. Lastly, they aid in identifying the unobservable impact of debt and business model decisions on bank expenses and the additional cost of debt faced by larger unrated banks.

The last group of moments tracks the interest rate levels and sovereign ratings generated by the model to ensure that they closely follow the actual behaviour in the economy. The discount factor is not estimated, rather it is set at 0.95, a level consistent with previous literature (De Nicolò et al., 2014).

5.5.3 MOMENTS, MODEL FIT AND PARAMETERS

Table 5.8 and Table 5.9 present the moments used in the estimation and compare the simulated with actual values. Figure 5.1 shows the behaviour of moments over time. Table 5.8 examine the averages across key time periods (100 moments) which are used for calculation of the standard errors and Table 5.9 displays the annual values (88 moments) which are used for checking the external validity of the model.[181] Overall, the model fit is highly satisfactory. Looking first at profitability, the model closely matches the actual ROE and ROA (Panel A of Table 5.8), but with slight over-prediction of the profitability at the end of the post-crisis period. The model also closely matches the returns on lending activity and returns on non-interest activities in the three periods and annually (Panel A of Table 5.9). The model correctly replicates the fall in non-interest activity during the financial crisis and the collapse in loan interest rates following 2008.

Secondly, the model accurately matches equity levels, capturing the overall rise throughout the sample and the dip during the European sovereign debt crisis. Similarly, for debt, the model captures the fall from 2006 to 2010 and the stabilization from 2011 onwards. This is reflected in the moments both in each period (Panel B of Table 5.8) and annually (Table 5.9). The model captures the trends in bank business model, which saw a proportional shift towards lending

[181] There are some additional unreported moments that are also used for external validity of the model.

activities in the first half (2005-2008) and then a shift to reduced lending activity in 2009-2015. The model also accurately matches the increase in capital ratios following the implementation of Basel II in 2006 (Table 5.9, Panel B). The model matches the dividends issued by banks, but slightly over predicts the proportion of share capital issued (Panel B of Table 5.8).

Thirdly, the model replicates the changing CRA behaviour throughout the sample, capturing the reduced credit ratings during the European sovereign debt crisis (Panel B of Table 5.9) and matching the standard deviation as well as the proportion of banks soliciting a rating from CRAs (Table 5.8, Panel C). The model correctly matches the cost of debt for rated and unrated banks and for banks that issue no extra debt in each period (Table 5.8, Panel C). The model also accurately matches the annual cost of debt for rated banks (Table 5.9, Panel B). The operating expenses incurred by banks is also matched for each period (Table 5.8, Panel C).

The parameters estimated using the DCDP method are reported in Table 5.10. Key unobservable parameters are the convex adjustment costs of debt ($\beta_{Ex,1}$), which is 0.079 times the percentage change in Debt squared, and of business model ($\beta_{Ex,2}$), which is 1.256 times the percentage change in GL-TEA. The larger nature of the costs is due to two factors, firstly the percentage change in debt is typically much greater than the change in business model and hence due to the square term in Eq. (5.17), this amplifies the difference. Secondly, a change in business model will result in a more radical shift in a bank's business practices and as such may require more reorganisation (e.g. new staff with different expertise) than simply increasing their size. Additionally, the Chapter estimates the theoretical cost of insolvency to be 69 times the firm equity, which does not simply encapsulate the firm's financial insolvency costs but also the very strong aversion of shareholders to insolvency.

5.6 SIMULATED EXPERIMENTS

This Section develops applications of the model which provide insights on the link between banks and the real economy. During the financial crisis, several complex financial institutions failed, which exacerbated the crisis and caused significant damage to the economies of European countries. To mitigate against repeats of this crisis, regulators designed and implemented a number of new regulations. These efforts can be classified into three distinct areas: (i) a bail-in regime, (ii) capital requirement regulations (Basel III) and (iii) reforming the credit rating industry. The following sub-sections run counterfactual scenarios that examine the impact of each regulatory effort in turn on bank decision-making behaviour in the real economy. The Chapter particularly focuses on how the various regulatory efforts affect banks' performance and behaviour, including: lending activity, profitability, insolvency, cost of debt and systemic impact.

5.6.1 BAIL-IN REGIME

This Section speaks to the influence of bailout and bail-in upon banks' behaviour in the real economy, e.g. lending and systemic risk. In the aftermath of the financial crisis, there was much criticism of decisions to bail-out banks, with association to an increase in banks' risk-taking behaviour (Dam and Koetter, 2012) and an increase in sovereign credit risk (Acharya et al., 2014). DeYoung et al. (2013) show that increased confidence in a bail-out makes bank's debt holders more risk insensitive, reduces bank's exposure to market discipline and encourages bank managers to take greater insolvency risks. European regulators decided to establish a new bail-in regime (from January 2015) as part of the European Banking Union.

This new European regulation shifts the penalty for bankruptcy from the tax payer, through government bailouts, to equity holders first and creditors second.[182] The result being that both shareholders and junior creditors will stand to lose more should the bank become insolvent,

[182] The mechanism of the European bail-in is as follows: The bail-in is triggered when a bank suffers a loss of >8% of its assets. This causes a write-down of assets to occur, principally the equity and subordinated debt. Once the write-down has occurred, the bank is recapitalised to 10.5% common equity capital ratio (CET1) through the conversion of the remaining subordinated debt and part of the senior unsecured debt. In effect, this causes the losses of the bank to first be taken by shareholders and then by its creditors (see Hüser et al., 2018).

thereby having increased “skin in the game”. With more at stake, increased concerns of shareholders will act to rein in banks’ risk-taking activity.

However, there is currently no consensus on how best to design or amend such a regime. The bail-out of two Italian banks in June 2017, for example, raised concerns on the effectiveness of the European bail-in regime. Berger et al. (2018) highlight the US regulatory debate on replacing the bail-in requirement for large bank holding companies. Yet, preliminary evidence from other studies is positive. Hilscher and Raviv (2014) indicate that the bail-in could be an effective tool for stabilizing financial institutions. Attaoui and Poncet (2015) show that firms’ total market values are larger in the presence of bail-in mechanisms. The introduction of the bail-in reduces the safety net for banks and should, through increased insolvency costs, result in lower insolvency rates and a reduced cost to governments (Conlon and Cotter, 2014) and hence taxpayers, resulting in a positive social outcome.

In the first counterfactual scenario the question: “what would have been the impact of the presence of the bail-in regime before and during the financial crisis?” is asked. To simulate this scenario in the model, the theoretical cost of insolvency for a bank is increased. Figure 5.2 illustrates the impact of a 50% and 20% increase in the theoretical cost of insolvency. [183] The 50% increase elicits consistent changes, but larger in magnitude than those for the 20% increase.

This Section discusses the impact of a 50% increase in the theoretical cost of insolvency. There is an initial adjustment period (2005-2007) where banks make several changes. In response to the bail-in, banks increase their capital ratios by 0.15%, consistent with Berger et al. (2018). This is achieved through the reduction in debt levels (0.045%, see Figure 5.2h), to prevent the occurrence of insolvency. Consistent with the reduction in debt levels, a fall in the percentage that choose to be rated (~1.5%, see Figure 5.2d) is observed, as the need to access debt markets drops. There is a slight spike in profits caused by lower adjustment costs as fewer banks choose to make large increases to their debt. This initial profit spike causes an increase in retained earnings which results in a boost to equity levels (0.04%, see Figure 5.2g).

Following the initial adjustment period (2008 onwards), banks maintain a new higher optimal capital ratio, which is consistent with Berger et al. (2018) and Leanza (2018), achieved by reducing debt levels by 0.045% (Figure 5.2h). Due to reduced leverage, banks achieve slightly lower profit levels, or ROE by around 0.05 to 0.1% (Figure 5.2a). The lower profits result in

[183] 1%, 5%, 10% and 100% adjustments are also examined and produce coherent results (see Figure A. 5.3).

less retained earnings and equity levels fall over time. To maintain the new optimal capital ratio, banks are required to decrease debt correspondingly. Consistent with the reduction in debt levels, a fall in the percentage of banks that choose to obtain a rating from CRAs is observed (by 1.5%, Figure 5.2d), as the need to access debt markets reduces. Due in part to the increased capital ratio, a reduction in the number of insolvent banks during the 2008 financial crisis is observed (approx. 5% lower, Figure 5.2e). This result is consistent with Dam and Koetter (2012), that a change in bailout expectations can impact the probability of bank distress.

Further, Figure 5.2c shows a slight decrease in credit rating levels (1%, equivalent to a 0.13 notch downgrade) which is unlike the 3-4 notch decrease predicted by Henriques' (2011) survey of European banks. This slight decrease appears to be caused by increased portfolio risk but is somewhat mitigated by the increased capital ratios. An important point to note is that banks are shifting their business activities more aggressively to seek higher profits. Figure 5.2f provides a very clear downward trend in lending. This increased shifting of activities is an attempt to counter the falling profits caused by reduced leverage and indicates that banks will seek to maximise their profit through other avenues.

In summary, the increased cost of insolvency causes banks to shift to adopt higher optimal capital ratios, which ensures a decrease in the frequency of insolvency. However, there are indications of a shift away from lending, which is associated with maintaining profit levels. This strongly suggests that the bail-in mechanism may affect lending in the real economy. The result is stronger for a greater increase in perceived insolvency costs.

5.6.2 CAPITAL REQUIREMENT REGULATIONS

This Section addresses the effects of capital adequacy regulations on lending and other aspects of bank behaviour. During the financial crisis, many banks were undercapitalised and there was substantial evidence that well capitalised banks demonstrated better performance (Berger and Bouwman, 2013; Miles et al., 2013). Over the past decade, there has been a substantial change in the approach to capital requirements. In Europe, regulators strengthened capital requirements by adopting Basel II which brought in a common equity tier 1 capital ratio of 2% in 2006,[184]

[184] EU Directive 2006/49/EC of 14th June 2006.

and then by adopting Basel III in 2013 which raises the level to 4.5% with an additional capital conservation buffer of 2.5%, bringing the total common equity ratio to 7.0%.[185]

Academics have also argued that banks should be financed with more equity (Bhagat and Bolton, 2014) and questioned whether the existing regulation goes far enough (Miles et al., 2013). In this analysis, the Section considers the following counterfactual scenarios: ‘‘how would banks’ behaviour have differed if the Basel III CET1 requirement of the initial 4.5% or the full 7% had been in place since 2005?’’. The results are reported in Figure 5.3.

Firstly, under the 4.5% CET1 simulated scenario, there is an initial adjustment period (2008 onwards) whereby banks adopt higher capital ratios by 0.3% (Figure 5.3b), which is double that stimulated by the baseline bail-in case in Section 5.6.2. This is driven by a reduction in debt levels by 0.4% (Figure 5.3h). A fall in profits by 0.25% is reported (Figure 5.3a), caused by lower leverage and the adjustment costs associated with hastily reducing the debt held to comply with the regulation. However, after the initial adjustment period, under the capital requirement regime, a notably different result is reported, whereby capital ratios trend back towards those of the original model (Figure 5.3b). This is driven by a steady increase in debt and contrasts starkly with the effects of the bail-in where, following the initial adjustment period, capital ratios remain at the new optimal level for the subsequent period. This implies that capital regulation merely constrains bank capital ratios and does not impact the underlying risk-taking behaviour. Higher credit ratings by 2-3% is observed (equivalent to a third of a notch, Figure 5.3c), which are warranted due to a large drop in the number of insolvent banks (40% less, Figure 5.3e) as banks perform much better during the two crisis periods.

Consistent with the case of the bail-in regime, a 4.5% CET1 requirement causes banks to increasingly shift business away from lending (Figure 3f). This increase in asset risk contrasts with Furlong and Keeley (1989), who argued that regulatory capital requirements did not lead value-maximizing banks to hold a riskier asset portfolio.

The second simulated scenario of 7.0% CET1 requirement elicits consistent, yet stronger results. Figure 5.3 shows a rise in banks’ average equity to total assets of 0.8%, a fall in profits of 0.5% and a corresponding fall in equity of 0.2% and debt levels of 0.7% at the end of the implementation period. Much stronger bank stability during the two crises is reported, with the

[185] EU No 575/2013 Article 92 of 26th June 2013. Initially CET1 levels were set at 3.5% and were slowly raised to 4.5% with an additional 2.5% capital conservation buffer (www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf).

number of insolvent banks falling by up to 60%. Further, the corresponding fall in capital ratios and rise in debt levels are consistent. Notably, unlike the first scenario of 4.5% CET1, the number of banks that chooses to be rated fall dramatically as banks lower their debt levels more substantially and require less access to capital markets. Bank ratings are also much more sensitive to the European sovereign debt crisis, because due to banks' increased capital, country level factors become increasingly important in determining the bank ratings. The prior impact on the real economy is further strengthened in the second scenario as banks switch more rapidly away from lending.

To summarise, if the Basel III capital requirements of 4.5% and 7% had been in place since 2005, the impact on bank behaviour would have been substantial. It would have resulted in larger increases in bank capital ratios and a greater decrease in bank debt (2-5 times greater than that elicited by the presence of a bail-in regime). This reform also triggers stronger bank stability during the two crises, with a lower number of insolvent banks. However, unlike the effect of the bail-in (which results in a new equilibrium), the impact of more stringent capital requirements diminishes following the initial adjustment period and does not result in a new equilibrium. Crucially, banks seek alternative ways to maintain profitability, which has a determinant effect on lending activity.

5.6.3 CHANGE IN CREDIT RATING BEHAVIOUR

This Section addresses the impact of shocks to bank debt and deposits. CRAs were widely criticised for their role in the financial crisis, and regulators were left in no doubt that inflated ratings had a significant impact (Bolton et al., 2012). Consequently, recent regulatory changes in the EU (CRA I, II and III) and in the US (Dodd-Frank Act) have targeted CRAs and their behaviour. Greater oversight of CRAs has, particularly in the EU, arguably resulted in increased *rating conservatism* (i.e. unjustifiably lower ratings). This arises as CRAs lower their ratings as a reaction to the increased scrutiny and to the potential penalties for over-rating (Bannier et al., 2010). It is important to consider how a change in CRA rating behaviour can spill over and impact the behaviour of the issuers (banks) they rate. In modelling this shock to bank debt/deposits, the following counterfactual scenarios are considered: (i) an increase in *rating conservatism*, whereby the case that bank ratings are 1-notch lower is examined and (ii) increasingly lenient CRAs which issue higher credit ratings, whereby the case that bank ratings are 1-notch higher is examined.[186]

In the first scenario, more conservative CRAs, which issue 1-notch lower ratings, raise the cost of debt for banks by 0.05-0.1% (Figure 5.4e). Following an initial adjustment period, banks are almost 50% less likely to choose to solicit a rating from CRAs (Figure 5.4d). Since credit ratings significantly impact banks' cost of debt, banks attempt to increase their rating by raising capital ratios (by 0.15% by the end of the sample, Figure 5.4a). Correspondingly higher levels of equity, an increase of 0.03% (Figure 5.4g), is observed. The effect is that, by the end of the sample, credit ratings are roughly equivalent to the original model.

In the second examined scenario, increasingly lenient CRAs issue 1-notch higher ratings, which lowers banks' cost of debt by 0.05% (Figure 5.4e), causing banks to solicit a rating from CRAs more often during non-crisis periods (Figure 5.4d). Banks also take advantage of the more lenient ratings by reducing their capital ratios by 0.075% at the end of the sample (Figure 4a). Although banks increase their debt more often, greater losses and increased insolvency rates during crisis periods (of up to 7%, Figure 5.4b) occur due to the reduced capital ratios. This increased insolvency rate leads to an overall decrease in equity and debt levels. Further, Figure 4f indicates that in both scenarios (conservative rating and lenient rating), the systematic change in rating practices adds to uncertainty for banks' lending activities and they increasingly shift towards non-interest income activities.

In summary, the simulated increase (decrease) in CRA conservatism predicts a corresponding increase (decrease) in a bank's cost of debt and reduces (increases) the proportion of banks that choose to solicit a rating. However, any systematic changes in rating practice add to uncertainty for banks' lending activity. Banks react to changes in CRA behaviour via their actions in the debt/deposit market and by the manipulation of their capital ratios, which can result in an increased rate of insolvency during crisis periods. The shock to debt/deposits induced by a change in CRA practices has a meaningful impact on banks' risk taking and hence their role in the economy.

[186] The chapter also examines 0.5 and 2-notch lower and higher rating and the results (see Figure A. 5.4) are consistent.

5.6.4 CHANGE IN THE MARKET SENSITIVITY TO CREDIT RATINGS

This Section addresses the impact of changing the market reliance on credit ratings. In the wake of the EU and US regulation, rating announcements, and in particular downgrades, have seen reduced market reactions. In particular, the EU has sought to reduce the markets dependence on credit ratings (see Chapter 3). As a result, the importance of credit ratings in determining bank's cost of debt might change. Both Chapter 3 and 4 find evidence of reduced market reactions to rating announcements, but there is little literature that examines how banks modify their behaviour in response to reduced market sensitivity of their rating. With this simulation I aim to explore the mechanism that drive the response of banks' behaviour.

Changing the importance of a credit rating in determining a bank's cost of debt will naturally impact how much a bank cares about its credit rating. Therefore, the expected result is for banks to change their behaviour accordingly: either maintain or bolster their rating (if it is more important) or reduce their efforts to be awarded a high credit rating (if it is less important). In modelling the changing importance of credit ratings, the following counterfactual scenarios are implemented: (i) a 20% increase in bank's cost of debt sensitivity to credit ratings, and (ii) a 20% decrease in sensitivity to credit ratings.

In the first scenario, a 20% increase in the sensitivity of cost of debt to credit ratings, raises the average rated cost of debt for banks by up to 4% (Figure 5.5e). Following an initial adjustment period, banks are 30% less likely to choose to solicit a rating from CRAs (Figure 5.5c). The increased sensitivity of cost of debt to credit ratings means that when the sovereign debt crisis hits, banks will go to greater lengths to protect falling credit ratings and raise capital ratios (by 0.4% by the end of the sample, Figure 5.5a). Equity levels fall to a new equilibrium, showing a decrease of 0.03% (Figure 5.5g). Due to the reduced number of banks soliciting ratings, rating levels are higher as the threshold at which it becomes beneficial to be rated is increased.

In the second examined scenario, a 20% decrease in the sensitivity of bank's cost of debt to ratings, lowers banks' average rated cost of debt by 1-3% (Figure 5.5e), causing banks to solicit a rating nearly 50% more by the end of the sample (Figure 5.5c). Surprisingly, banks do not immediately take advantage of the cheaper debt and initially reduce debt levels, which results in significantly stronger capital ratios (0.35%) during the 2008 crisis. However, at the onset of the EU sovereign debt crisis, which significantly impacted bank credit ratings, banks take advantage of the reduced market sensitivity to ratings by reducing their efforts to strengthen their capital ratios (Figure 5.5a). The initially higher levels of capital lead to reduced bank insolvency rates in the early part of the sample, but the latter behavioural change has no real impact on bank insolvency rates (Figure 5.5d). Interestingly, rating levels seem unaffected by the subsequent changes in behaviour (Figure 5.5b). Further, Figure 5.5f shows that the decreased sensitivity of bank's cost of debt, causes a significant shift (-0.7%) in banks away from lending activities and towards increased non-interest income activities, the largest impact on lending of the four counterfactual scenarios.

In summary, the increased (decreased) sensitivity of a bank's cost of debt to credit ratings predicts a corresponding increase (decrease) in a bank's cost of debt. This impacts the proportion of banks that choose to solicit a rating. In particular bank's response to the EU sovereign debt crisis (which impacted bank ratings through the sovereign-bank rating channel), by the manipulation of their equity to total assets. The changes in markets sensitivity to ratings once again has a meaningful impact on banks' risk taking and hence their role in the economy.

5.7 CONCLUSIONS

The 2008 financial crisis led to the collapse or restructuring of numerous important financial institutions, which exacerbated the crisis and caused further damage to European economies through sovereign-bank linkages. Recent European regulatory efforts have therefore sought to reform the banking industry and to mitigate bank risk-taking behaviour to prevent a future re-occurrence. To the best of my knowledge, this is the first study to build and estimate a dynamic model of bank behaviour and performance. The DCDP model is used to simulate counterfactual scenarios that examine the potential influence of pre-crisis adoption of (i) a European bail-in regime, (ii) Basel III capital requirements, (iii) the reform of the credit rating industry, and (iv) a change in the market sensitivity to credit ratings, on bank behaviour in the real economy. The model is matched to a sample of 6,121 banks from 27 EU countries for the period 2004 to 2015. A large number of key aspects in the data (100 moments) are replicated, including the average equity, debt financing, gross loans to total earning assets, capital ratios, return on equity and decision to solicit a rating over key periods.

Firstly, it is found that a bail-in regime (with increased costs of insolvency) leads to the adoption of higher optimal capital ratios and to a decrease in bank insolvency rates during crisis periods. Banks shift away from lending, which is associated with maintaining profit levels, i.e. the bail-in regime influences lending activity in the real economy. This effect scales with the perceived increase in insolvency costs and, crucially, results in a new equilibrium. Secondly, it is found that Basel III capital requirements (of 4.5% and 7%) lead to a stronger increase in bank capital ratios (0.3% and 0.8% higher respectively) driven by a fall in debt financing that results in stronger bank stability in the subsequent period (up to 60% fewer insolvent banks). There is evidence of diminishing returns with the effect of capital ratios on bank insolvency rates. While the effect is greater in magnitude compared to the bail-in scenario, it does not result in a new equilibrium and fails to stabilise during the sample period. A crucial insight is that banks seek alternative ways to maintain profitability, which has a determinantal effect on lending activity in the real economy. Thirdly, it is shown that banks compensate for changes in CRA practices via their manipulation of their capital ratios and their actions in debt/deposit markets. Any systematic changes in rating practices add to uncertainty for banks' lending activity, yet any increased leniency from CRAs may result in increased bank insolvency rates. Lastly, it is shown that an increased (decreased) sensitivity of the market to credit ratings (see Section 5.6.4), directly increases (decreases) bank's cost of debt. Bank's respond by reducing lending and being less likely to solicit a rating. Additionally, the increased (decreased) sensitivity causes the EU sovereign debt crisis to have a correspondingly greater (lesser) impact on bank's behaviour, by stimulating a greater (lesser) effort to manipulate their rating.

In general, the empirical results emphasise the importance of understanding the interactions between regulatory change and the dynamics of banks' decision-making and risk taking, and hence their role in the real economy. The dynamic framework allows one to capture and explore mechanisms and feedback processes that would simply not be possible to consider using a static framework, such as reduced form estimates.

The Chapter concludes that the implementation of the bail-in and the capital requirements have a positive impact by reducing bank insolvency rates, particularly during crisis periods and hence reduce the burden on governments and the real economy. Regulators should exercise caution when considering how capital requirements can potentially induce banks to shift business away from lending, and to seek other (potentially risker) means to maintain their profitability. Regulators should balance the reduction in insolvency rates (which exhibit diminishing returns) against the fall in bank sizes and profits. The findings imply a potentially effective method of mitigating banks' risk-taking by combining increased capital requirements with the introduction of a bail-in regime. The increased responsibility of equity holders for losses complements the increased "skin in the game" caused by greater levels of capital and is necessary to ensure a shift to a reduced risk-taking equilibrium. The reduction in risk and therefore insolvency should result in a lessening the burden on governments, on sovereign credit risk and thereby benefit the real economy. The results also imply that CRA reforms should deter increasing rating leniency, as it may lead to increased bank insolvency rates. Lastly, a change in the market sensitivity to credit rating can impact bank's decision to solicit a rating, reduce bank lending and result in increased insolvency during crisis periods.

TABLES

Table 5.1: Banks country distribution

Country	Number of banks
Austria	172
Belgium	179
Bulgaria	40
Cyprus	49
Czech Republic	71
Germany	851
Denmark	180
Estonia	23
Spain	337
Finland	85
France	769
Great Britain	780
Greece	44
Hungary	84
Ireland	128
Italy	1,120
Lithuania	17
Luxemburg	238
Latvia	34
Malta	37
Netherlands	172
Poland	224
Portugal	177
Romania	48
Sweden	181
Slovenia	42
Slovakia	39
Total	6,121

This is the number of banks in each country that is included in the data sample for illustrative analysis and simulation during the period of the period 2004 to 2015.

Table 5.2: Variables and equations

Panel A: Variable, symbols and data sources

Variable	Symbol	Source	Units	Description
Total assets	*TA*	BankScope	Euros	Total assets of the bank
Equity	*Eq*	BankScope	Euros	Equity of the bank
Debt	*D*	BankScope	Euros	Total Assets – Equity. Debt denotes both debt and deposits.
Gross loans to total earning assets	λ	BankScope	Ratio	The proportion of lending activities
Credit rating	*CR*	BankScope	Numerical Scale	Ratings from S&P, Moody's and Fitch. If ratings from multiple CRAs were available, the average was used
Rated	*Rated*	BankScope	Dummy	1 if bank is rated, zero otherwise
Return on loans	*X*	Calculated from data	Percentage	Return generated from loan activity
Return on non-interest activities	*Y*	Calculated from data	Percentage	Return generated from non-interest income activities
Net income	*NI*	BankScope	Euros	Net income generated by the bank.
Cost of debt	*COD*	Calculated from data	Percentage	Calculated as total interest expense/debt
Dividends	*Div*	BankScope	Euros	Dividends paid by the bank
Share capital	*SC*	BankScope	Euros	Calculated as the change in share capital
Financial crisis	*Ec*	VSTOXX	Index	European market volatility index.[187]
Sovereign rating	*SR*	S&P Capital IQ	Scale	S&P sovereign ratings
Interest rates	*IR*	DataStream	Percentage	Interest rates for each country and the Eurozone
Inflator		World Bank	Ratio	GDP inflator from the World Bank national accounts data

Panel B: Illustrative analysis equations

Dependent Variable	Equation
Credit rating	$CR_{i,t} = \beta_{CR,0}(1 - Rated_{i,t-1}) + \beta_{CR,1}CR_{i,t-1}Rated_{i,t-1} + \beta_{CR,2}Ec_{i,t} + \beta_{CR,3}SR_{i,t} + \beta_{CR,4}\lambda_{i,t} + \beta_{CR,5}\left(\frac{TA_{i,t}}{Eq_{i,t-1}}\right)^2 + \varepsilon_{CR,1}$
Return on loans	$X_{i,t} = \beta_{X,0} + \beta_{X,1}\left(\frac{Ec_{i,t} + Ec_{i,t-1} + Ec_{i,t-2}}{3}\right) + \beta_{X,2}IR_{i,t} + \beta_{X,3}SR_{i,t} + \varepsilon_{X,1}$
Return on non-interest activities	$Y_{i,t} = \beta_{Y,0} + \beta_{Y,1}SR_{i,t} + \beta_{Y,2}Ec_{i,t} + \varepsilon_{Y,2}$
Equity	$\Delta Eq_{i,t} = NI_{i,t} - \beta_{Eq,1}Div_{i,t} + \beta_{Eq,2}SC_{i,t}$
Dividends	$Div_{i,t} = \beta_{Div,1}Eq_{i,t-1} + \beta_{Div,2}NI_{i,t}$
Share capital	$SC_{i,t} = \beta_1 TA_{i,t}$
Expenses	$EXPS_{i,t} = \beta_{Ex,0}TA_{i,t} = \beta_{Ex,0}(Eq_{i,t-1} + D_{i,t})$
Cost of debt[188]	$COD_{i,t} = \beta_{COD,0} + \beta_{COD,1}IR_{i,t} + \beta_{COD,2}Ec_{i,t} + \theta_t * \left\{\beta_{COD,6}\left(\frac{TA_{i,t}}{Eq_{i,t}}\right) + \beta_{COD,7}\lambda_{i,t} + Rated_{i,t} * [\beta_{COD,4}CR_{i,t}] + (1 - Rated_{i,t}) * [\beta_{COD,8} + \beta_{COD,9}TA_{i,t} + \beta_{COD,10}SR_{i,t}]\right\}$

This table describes the data sources and definition of variables (Panel A) and equations estimated in the illustrative analysis (Section 5.3.1). θ is the proportional increase in debt.

[187] The VSTOXX is an index of 30-day option implied volatility in the EURO STOXX 50 indices and is designed to reflect the market expectations of volatility.

[188] For the purpose of the exploratory regressions a linear relationship is assumed between CR and cost of debt. The actual relationship however, appears to be exponential, with the change in bond spread between higher rating categories (e.g. AAA and AA) being much smaller than lower rating categories (e.g. BBB and BB). Hence the actual model employs an exponential relationship (shown in section 5.4.2).

Table 5.3: Summary statistics of the data sample

Variable	Obs	Mean	Standard Deviation	Min	Max
Equity	29,565	583,000,000	1,480,000,000	3,658,058	14,400,000,000
Debt	29,803	9,010,000,000	28,900,000,000	8,638,128	303,000,000,000
Total Assets	30,464	24,400,000,000	135,000,000,000	3,576,329	3,100,000,000,000
GL-TEA	26,728	0.616	0.274	0.003	1.009
Rating	6,418	12.677	2.953	1	18
X return	18,364	0.055	0.027	0.013	0.214
Y return	22,692	0.049	0.062	0.001	0.439
Cost of Debt	27,462	0.021	0.013	0.001	0.075
Dividends	7,731	54,500,000	135,000,000	0	1,100,000,000
Share Capital	25,226	9,819,635	43,700,000	-44,700,000	440,000,000
Economic Crisis	30,631	23.359	6.400	14.045	33.729
Sovereign rating	30,631	43.950	10.066	0	52
Interest Rates	30,631	0.019	0.017	-0.002	0.124
Return on Equity	24,509	0.067	0.105	-0.368	0.487
Expenses	8,162	505,000,000	2,490,000,000	1,286	49,800,000,000
Equity to Total Assets	29,509	0.126	0.120	0.011	0.819

Summary statistics for key variables. The sample consists of all the banks in in 27 EU countries during the period 2004 to 2015. See Table 5.2 for variables' definitions. The mean rating is the mean when not zero (as this is no rating).

Table 5.4: Rating scale

Panel A: Rating scale

S&P Rating	Moody's Rating	Fitch Rating	18-notch scale
AAA	Aaa	AAA	18
AA+	Aa1	AA+	17
AA	Aa2	AA	16
AA-	Aa3	AA-	15
A+	A1	A+	14
A	A2	A	13
A-	A3	A-	12
BBB+	Baa1	BBB+	11
BBB	Baa2	BBB	10
BBB-	Baa3	BBB-	9
BB+	Ba1	BB+	8
BB	Ba2	BB	7
BB-	Ba3	BB-	6
B+	B1	B+	5
B	B2	B	4
B-	B3	B-	3
CCC+/CCC/CCC-	Caa1/Caa2/Caa3	CCC	2
CC/C/SD	Ca/C/D	CC/C/D	1

Panel B: Distribution

S&P		Moody's		Fitch	
Category	Frequency	Category	Frequency	Category	Frequency
AAA	55	Aaa	64	AAA	27
AA+	40	Aa1	138	AA+	39
AA	115	Aa2	214	AA	96
AA-	1395	Aa3	314	AA-	1277
A+	1572	A1	295	A+	2234
A	572	A2	407	A	461
A-	259	A3	279	A-	278
BBB+	188	Baa1	231	BBB+	255
BBB	159	Baa2	188	BBB	187
BBB-	126	Baa3	182	BBB-	149
BB+	86	Ba1	110	BB+	141
BB	74	Ba2	86	BB	71
BB-	55	Ba3	77	BB-	97
B+	34	B1	42	B+	31
B	24	B2	44	B	30
B-	9	B3	43	B-	28
C	0	Caa1	27	CCC	16
CC	2	Caa2	25	CC	3
CCC+	6	Caa3	16	C	2
SD	8	Ca	9	D	15
		C	9		
Total	4779	Total	2800	Total	5437

How the ratings are mapped to an 18-notch rating scale and the distribution of ratings in the sample.

Table 5.5: Ratings and returns

Panel A: Return on loans

	OLS		OLS		OLS		OLS	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Interest rate	56.314***	2.59	0.573***	30.16	56.314***	2.59	0.606***	31.41
Financial crisis moving average	-0.849**	-2.49	-0.0002***	-3.66				
Financial crisis					0.120**	2.49	-0.0003***	-7.50
Sovereign rating	0.003**	2.41	0.00007*	1.79	0.003**	2.41	0.00008*	1.85
Constant	17.115**	2.49	0.045***	25.13	-2.988**	-2.46	0.047***	26.25
Country * Year	Yes		No		Yes		No	
Observations	18,364		18,364		18,364		18,364	
R^2	29.4%		12.5%		29.4%		12.7%	

Panel B: Return on non-interest activities return

	OLS		OLS	
	Coeff	t-stat	Coeff	t-stat
Sovereign rating	-0.005	-1.29	0.0003***	3.54
Financial crisis	-0.009*	-1.87	-0.0004***	-6.43
Constant	0.445*	1.68	0.047***	14.56
Country * Year FE	Yes		No	
Observations	22,692		22,692	
R^2	5.3%		0.4%	

Panel C: Credit rating

	Ordered Logit		Ordered Logit	
	Coeff	z-stat	Coeff	z-stat
Not Rated	32.193***	28.40	27.578***	30.76
Rating	2.484***	34.55	2.098***	37.36
Financial crisis level	-0.219*	-1.65	0.007**	2.20
Sovereign Rating	-0.290***	-2.61	0.063***	14.12
Total assets to equity squared	5e-07	0.41	2e-07	0.78
Gross Loans to total earning assets	-0.311***	-2.87	-0.130	-1.30
Country * Year FE	Yes		No	
Observations	5,597		5,597	
R2	52.4%		46.8%	

*This table reports the results of regressions that examine the underlying relationship for return on loans (Panel A), return on non-interest income (Panel B) and credit rating levels (Panel C) using a sample of EU banks during 2005 to 2015. For equations and variables' definitions, see Table 5.2. 18-notch numerical credit rating scale is used (AAA/Aaa = 18, AA+/Aa1 = 17 … CCC+/Caa1/CCC/Caa2/, CCC-/Caa3 = 2, C/SD/CC/D = 1). 'Not Rated' is a dummy that takes a value of 1 when the firm is not rated and zero when rated. Country and year interacted fixed effects are included and standard errors are clustered by bank and ***, **, * represent significance at 1%, 5% and 10% respectively.*

Table 5.6: Equity, dividends and share capital

Panel A: Equity

	OLS		OLS		OLS	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Net Income	1.205***	5.99	1.169***	6.00	1.206***	5.99
Dividend Paid	-1.150***	-3.70	-1.118***	-3.69	-1.151***	-3.70
Change in share capital	0.419***	3.53	0.408***	3.55	0.419***	3.53
Constant	1.357e+08	1.06	-8202043*	-1.96		
Country *Year	Yes		No		Yes	
Observations	6,637		6,637		6,637	
R-squared	27.9%		26.3%		28.7%	

Panel A: Dividends

	OLS		OLS	
	Coefficient	t-stat	Coefficient	t-stat
Equity	0.004*	1.87	0.005**	2.10
Net Income	0.390***	12.57	0.405***	13.48
Country *Year	Yes		No	
Observations	6,976		6,976	
R-squared	58.9%		56.6%	

Panel C: Share capital

	OLS		OLS		OLS	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Total Assets	0.002***	5.94	0.002***	6.04	0.002***	5.94
Constant	-1,441,671	-0.16	-1,325,922	-0.27		
Country *Year	Yes		No		Yes	
Observations	24,022		24,022		24,022	
R-squared	4.9%		4.9%		5.0%	

*This table presents the results of the regressions that model the change in equity, using a sample of EU banks during 2005 to 2015. The dependent variables are equity, dividends and share capital for Panel A, B and C respectively. For equations and variables' definitions, see Table 5.2. Country and year interacted fixed effects are included and standard errors are clustered by bank and ***, **, * represent significance at 1%, 5% and 10% respectively.*

Table 5.7: Expenses, adjustment costs and tax

Panel A: Banks' expenses

	OLS		OLS		OLS		OLS	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Total assets (t)	0.010***	11.49	0.010***	11.49	0.011***	12.97	0.010***	12.12
Constant			1.255e06	0.32			6.441e07***	10.44
Country * Year	Yes		Yes		No		No	
Observations	7,632		7,632		7,632		7,632	
R-squared	40.0%		34.2%		38.1%		33.3%	

Panel B: t-test of expenses and adjustment costs

		Expenses to Total Assets			
		No change	Large change	Difference	t stat
Debt	Obs	2,494	813		
	Coef	2.619%***	3.773%***	1.154%***	9.04
Business Model	Obs	2,079	959		
	Coef	2.654%***	2.885%***	0.231%**	2.10

Panel C: Cost of debt regressions

	OLS		OLS		OLS		OLS	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
IR	2.314	1.56	0.887	0.55	0.420***	55.41	0.420***	27.94
Rating	-0.001***	-2.80	-0.003***	-3.89	-0.001***	-2.74	-0.004***	-4.98
Not rated	-0.026***	-6.04	-0.036***	-4.06	-0.033***	-7.48	-0.046***	-4.93
Financial Crisis	0.003	1.03	0.0001	0.03	0.00002	1.58	0.0001***	5.29
Total Assets to Equity	-2e-07	-0.03	0.00003	0.85	8e-06	0.79	0.00005*	1.81
Gross Loans to Total Earning Assets	0.041***	13.77	0.040***	6.64	0.026***	9.19	0.026***	4.57
Sovereign Rating	-0.0002**	-2.34	-0.00006	-0.32	0.00006	0.66	0.0003*	1.81
Constant	-0.074	-0.95	0.005	0.05	0.013***	40.82	0.014***	21.62
Country * Year	Yes		Yes		No		No	
Bank rated at some point	No		Yes		No		Yes	
Observations	19,923		5,651		19,923		5,651	
R-squared	46.7%		44.4%		33.4%		31.2%	

*Panel A presents the results of OLS regressions that model banks' expenses, using a sample of EU banks during 2005 to 2015. Panel B shows a t-test of expenses to total assets ratio (%) for banks with and without a large change in debt or business model. Panel C present the results of regressions that model banks cost of debt. For equations and variables' definitions, see Table 5.2. Country and year interacted fixed effects are included and standard errors are clustered by bank and ***, **, * represent significance at 1%, 5% and 10% respectively.*

Table 5.8: Table of moments

Panel A: Profitability, return on loans and non-interest activity return

Moment	Pre-Crisis (2006)		Peak Crisis (2007-2010)		Post Crisis (2011-2015)	
	Simulated	Actual	Simulated	Actual	Simulated	Actual
Return on Equity (%)	10.79	10.95	7.25	7.07	6.35	5.01
	(19.06)	(9.94)	(16.32)	(10.27)	(14.60)	(10.28)
Return on Assets (%)	1.00	0.98	0.75	0.66	0.76	0.57
	(1.78)	(1.14)	(1.63)	(1.17)	(1.60)	(1.31)
Return of X (%)	6.82	6.46	5.95	6.03	4.31	4.79
	(2.87)	(2.98)	(2.92)	(2.73)	(2.88)	(2.44)
Return of Y (%)	5.98	5.21	5.57	4.81	5.46	4.90
	(4.95)	(6.06)	(4.75)	(5.96)	(5.04)	(6.21)

Panel B: Bank characteristics and behaviour

Moment	Pre-Crisis		Peak Crisis		Post Crisis	
	Simulated	Actual	Simulated	Actual	Simulated	Actual
Equity	18.66	18.58	18.71	18.60	18.73	18.55
	(2.08)	(1.76)	(2.14)	(1.76)	(2.18)	(1.82)
Debt	20.83	20.82	20.71	20.83	20.56	20.66
	(2.62)	(2.09)	(2.47)	(2.10)	(2.32)	(2.11)
Business Model (%)	65.32	61.94	66.86	63.53	59.81	60.95
	(25.78)	(27.77)	(22.85)	(27.70)	(21.42)	(26.34)
Equity to Total Assets (%)	12.01	11.82	13.09	12.36	14.78	13.10
	(6.87)	(11.00)	(6.05)	(11.95)	(6.15)	(12.36)
Dividends (% of TA)	0.76	0.63	0.77	0.62	0.85	0.53
	(0.47)	(0.96)	(0.39)	(1.16)	(0.37)	(0.97)
Share Capital (% of Equity)	3.90	0.38	3.28	1.11	2.84	1.46
	(2.13)	(2.91)	(1.57)	(2.93)	(1.12)	(3.08)
Solvency (%)	99.75	100.00	98.82	97.80	99.49	95.83

Panel C: Credit ratings, cost of debt and expenses

Moment	Pre-Crisis		Peak Crisis		Post Crisis	
	Simulated	Actual	Simulated	Actual	Simulated	Actual
Average rating	13.55	13.30	13.16	13.22	11.74	11.94
	(3.05)	(2.50)	(3.07)	(2.66)	(3.26)	(3.20)
Rated / Total (%)	14.16	10.82	12.88	12.70	9.78	11.90
Cost of Debt - rated (%)	2.77	2.46	2.66	2.95	1.60	1.66
	(0.47)	(1.00)	(0.68)	(1.45)	(0.31)	(1.24)
Cost of Debt – unrated (%)	2.05	2.44	2.13	2.79	1.31	1.57
	(0.44)	(1.08)	(0.62)	(1.47)	(0.34)	(1.14)
Cost of Debt – no extra debt (%)	2.40	2.75	2.41	2.89	1.52	1.90
	(0.34)	(1.18)	(0.57)	(1.43)	(0.27)	(1.27)
Expenses (% of total assets)	Na	Na	2.72	2.93	2.48	2.93
	Na	Na	(1.25)	(3.34)	(1.18)	(3.34)

Panel D: Wider economy

Moment	Pre-Crisis		Peak Crisis		Post Crisis	
	Simulated	Actual	Simulated	Actual	Simulated	Actual
IR (%)	4.37	2.98	3.20	2.90	0.67	0.74
Sovereign rating	47.15	46.99	45.83	46.30	40.41	40.35

This table shows the mean values and the standard deviations (in brackets) for the simulated and actual moments. Data on expenses was not available in the pre-crisis period. The data sample includes EU banks from 2005 to 2015. See Table 5.2 for variables' definitions.

Table 5.9: Table of annual moments

Panel A: Credit ratings, ROE, return on loans and return on non-interest activities

Moment	Credit Rating		ROE (%)		Return on loans (%)		Return on non-interest activities (%)	
	Simulated	Actual	Simulated	Actual	Simulated	Actual	Simulated	Actual
2005	14.25	13.23	10.39	11.23	6.22	6.80	6.15	5.63
2006	12.57	13.38	10.79	10.95	6.82	6.46	5.98	5.21
2007	13.31	13.38	9.86	10.77	6.96	6.89	5.90	5.25
2008	13.18	13.50	7.12	6.56	6.96	7.04	5.42	4.47
2009	13.09	13.19	5.55	5.57	5.22	5.48	5.35	4.73
2010	13.46	12.83	6.52	5.34	4.65	4.90	5.60	4.76
2011	12.68	12.72	3.76	4.81	4.34	5.08	5.15	4.78
2012	12.61	12.24	5.62	4.65	4.31	5.05	5.36	4.99
2013	11.81	11.64	7.51	4.76	4.27	4.76	5.69	4.97
2014	10.90	11.42	7.92	5.39	4.30	4.63	5.66	5.06
2015	11.10	11.53	6.95	5.51	4.34	4.40	5.41	4.67

Panel B: Cost of debt, debt, equity and capital ratio

Moment	Cost of debt – rated (%)		Debt (log)		Equity (log)		Equity to total assets (%)	
	Simulated	Actual	Simulated	Actual	Simulated	Actual	Simulated	Actual
2005	2.41	2.46	20.80	20.68	18.60	18.46	11.96	12.64
2006	2.77	2.76	20.83	20.82	18.66	18.58	12.01	12.45
2007	2.94	3.34	20.76	20.86	18.69	18.60	12.83	12.74
2008	3.40	3.58	20.75	20.82	18.71	18.54	12.82	12.69
2009	2.57	2.51	20.69	20.83	18.70	18.61	13.23	12.98
2010	1.91	2.06	20.67	20.80	18.72	18.63	13.47	13.54
2011	1.99	2.11	20.57	20.65	18.70	18.49	14.24	13.90
2012	1.74	2.18	20.54	20.65	18.70	18.50	14.61	14.11
2013	1.54	1.75	20.56	20.65	18.73	18.54	14.69	14.48
2014	1.47	1.53	20.56	20.62	18.75	18.55	15.08	14.40
2015	1.70	1.29	20.57	20.75	18.77	18.71	15.27	14.05

The average of various annual characteristics generated by the model and those observed in the actual data. The data sample includes EU banks from 2005 to 2015. See Table 5.2 for variables' definitions.

Table 5.10: Parameters

Panel A: Credit rating, return on loans and return on non-interest activities

Group	Variable	Parameter	Value	Standard error
Credit rating	$(1\text{-}Rated_{i,t-1})$	$\beta_{CR,0}$	4.800***	0.263
	$Rated_{i,t-1}$	$\beta_{CR,1}$	0.255**	0.005
	$Ec_{i,t}$	$\beta_{CR,2}$	-0.010***	0.013
	$SR_{i,t}$	$\beta_{CR,3}$	0.277***	0.005
	$\lambda_{i,t}$	$\beta_{CR,4}$	-4.698***	0.276
	$\left(\frac{TA_t}{Eq_{t-1}}\right)^2$	$\beta_{CR,5}$	-0.001***	0.0005
	CR shock	$\varepsilon_{CR,1}$	1.000***	0.054
Return on loans	Constant	$\beta_{X,0}$	0.009***	0.00008
	$Ec_{i,t}$	$\beta_{X,2}$	-0.0001***	0.00001
	$IR_{i,t}$	$\beta_{X,3}$	0.609***	0.002
	$SR_{i,t}$	$\beta_{X,4}$	0.0003***	0.000001
	X shock	$\varepsilon_{X,1}$	0.012***	0.00009
Return on non-interest activities	Constant	$\beta_{Y,0}$	0.009***	0.00008
	$SR_{i,t}$	$\beta_{Y,1}$	0.001***	0.000002
	$Ec_{i,t}$	$\beta_{Y,2}$	-0.0003***	0.000001
	Y shock	$\varepsilon_{Y,1}$	0.022***	0.00005
	Covariance of X shock and Y shock	$Cov(\varepsilon_{X,1}, \varepsilon_{Y,1})$	0.107***	0.006

Panel B: Equity, dividends and share capital

Group	Variable	Parameter	Value	Standard error
Equity	*Div*	$\beta_{Eq,0}$	0.946***	0.068
	SC	$\beta_{Eq,1}$	0.409***	0.013
	Debt decay	*D_decay*	0.066***	0.002
Dividends	Eq_{t-1}	$\beta_{Div,0}$	0.055***	0.002
	NI_t	$\beta_{Div,1}$	0.083***	0.003
Share capital	TA_t	$\beta_{SC,0}$	0.004***	0.00006

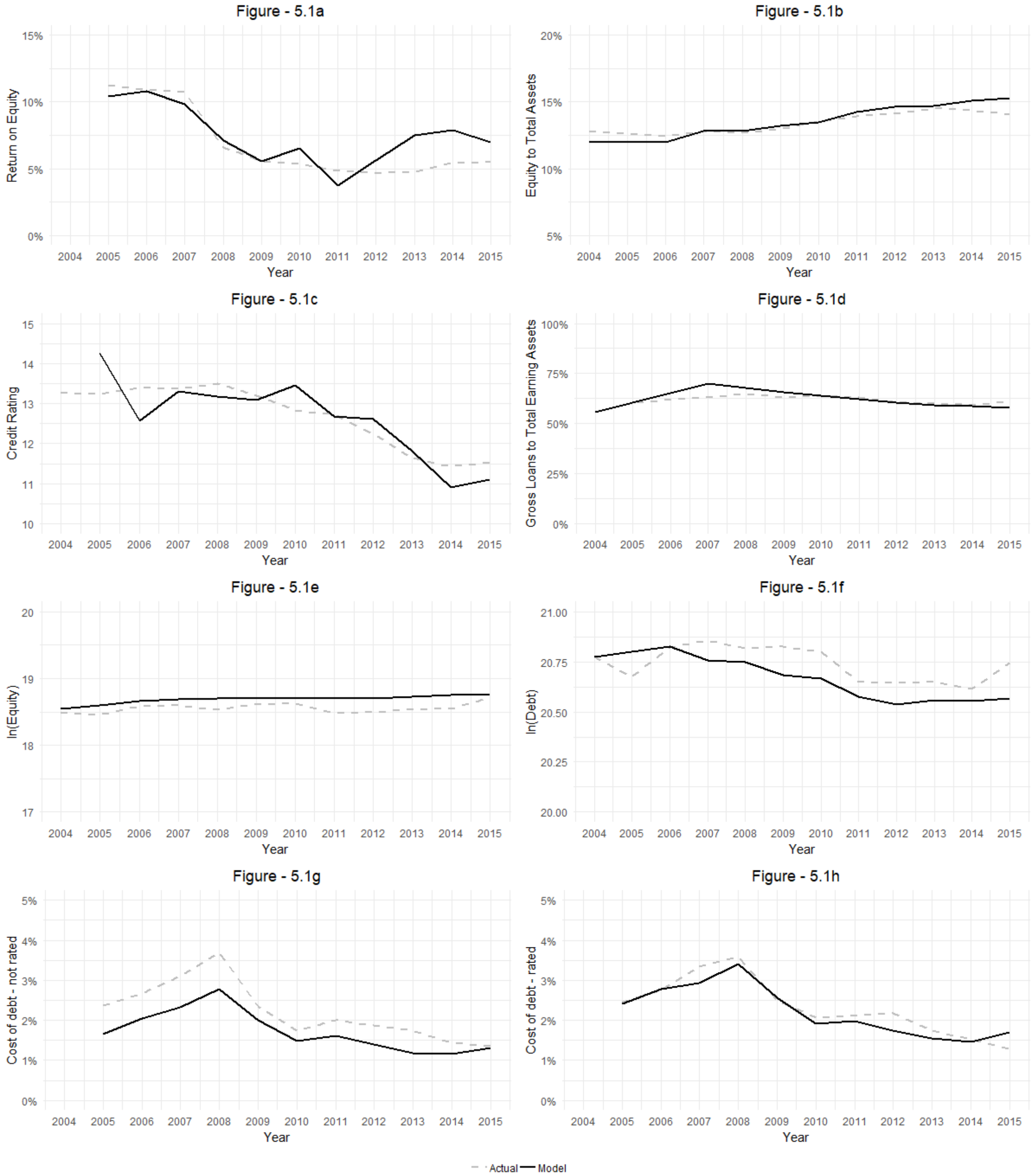
Panel C: Expenses, tax, cost of debt and insolvency

Group	Variable	Parameter	Value	Standard error
Expenses	TA_t	$\beta_{Ex,0}$	0.010***	0.00002
	$[\beta_{D,1}(\tilde{D}_t)]^2$	$\beta_{Ex,1}$	0.079***	0.00005
	$[\beta_{\lambda,1}(\tilde{\lambda}_t)]^2$	$\beta_{Ex,2}$	1.256***	0.0002
	Expenses shock	$\varepsilon_{Ex,1}$	0.008***	0.008
Corporate Tax	T	$\beta_{Tax,0}$	0.289***	0.001
Cost of debt	Constant	$\beta_{COD,0}$	0.009***	0.00008
	$IR_{i,t}$	$\beta_{COD,1}$	0.306***	0.0003
	$Ec_{i,t}$	$\beta_{COD,2}$	0.0004***	0.000002
	Credit rating adjustment constant	$\beta_{COD,3}$	-0.005***	0.0001
	Credit Rating linear parameter	$\beta_{COD,4}$	0.208***	0.003
	Credit Rating exponential parameter	$\beta_{COD,5}$	-0.240***	0.006
	$\left(\frac{TA_{i,t}}{Eq_{i,t}}\right)$	$\beta_{COD,6}$	0.000***	0.000004
	$\lambda_{i,t}$	$\beta_{COD,7}$	0.011***	0.001
	$(1\text{-}Rated_{i,t})$	$\beta_{COD,8}$	-0.039***	0.001
	$(1\text{-}Rated_{i,t})\times TA_{i,t}$	$\beta_{COD,9}$	6.95E-14***	0.000
	$(1\text{-}Rated_{i,t})\times SR_{i,t}$	$\beta_{COD,10}$	0.003***	0.00010
Insolvency cost	Insolvency cost	$\beta_{Insolv,1}$	68.911***	9.371

This table displays the estimated structural parameters estimated with their standard errors and t statistics. The parameters correspond to the symbols used in the theoretical model (see Section 5.4). See *for variables' definitions. ***, **, * represent significance at 1%, 5% and 10%* respectively.

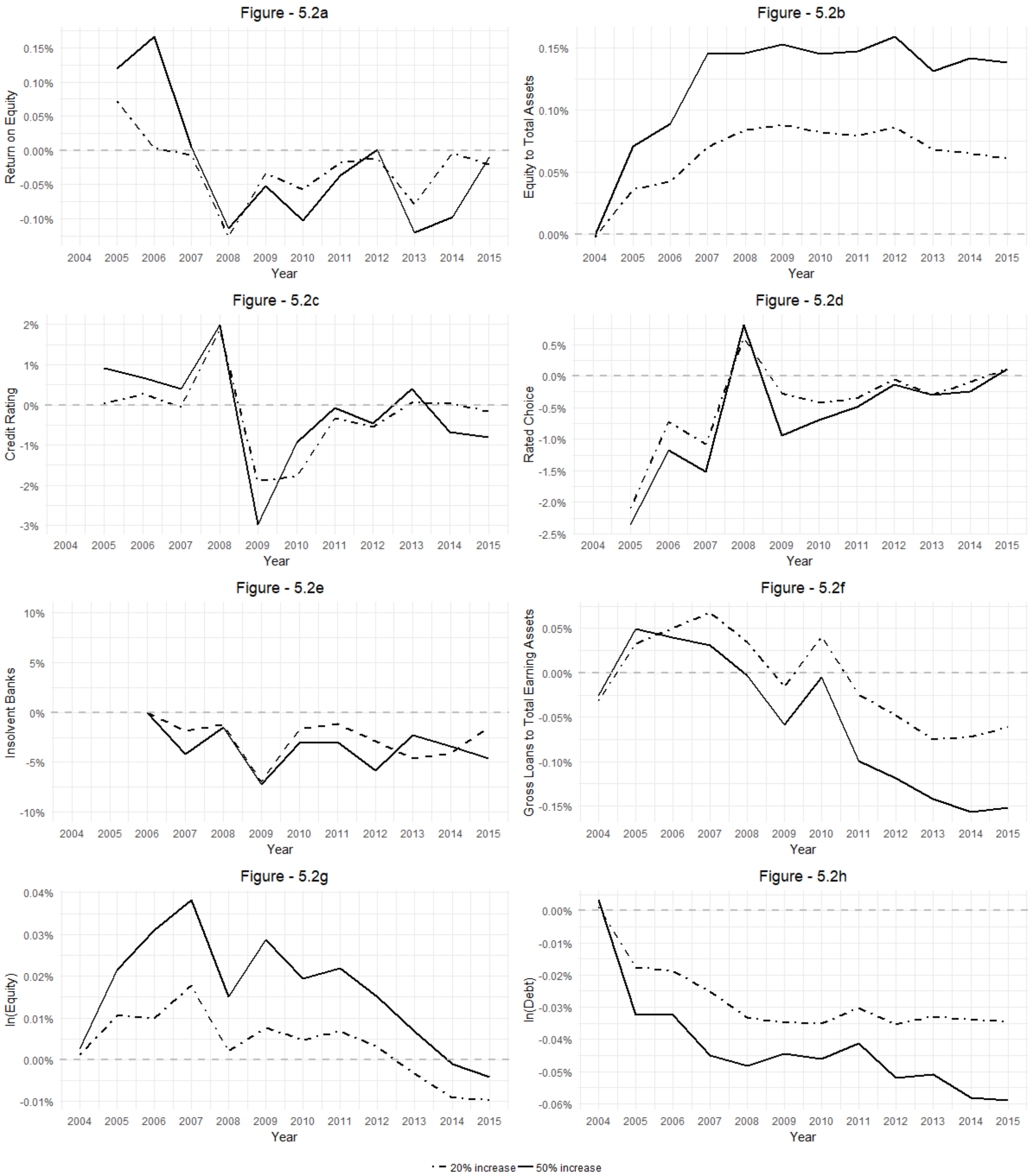
FIGURES

Figure 5.1: The behaviour of variables over time



The figure shows the change in the various bank characteristics over time. See Table 5.2 for variables' definitions.

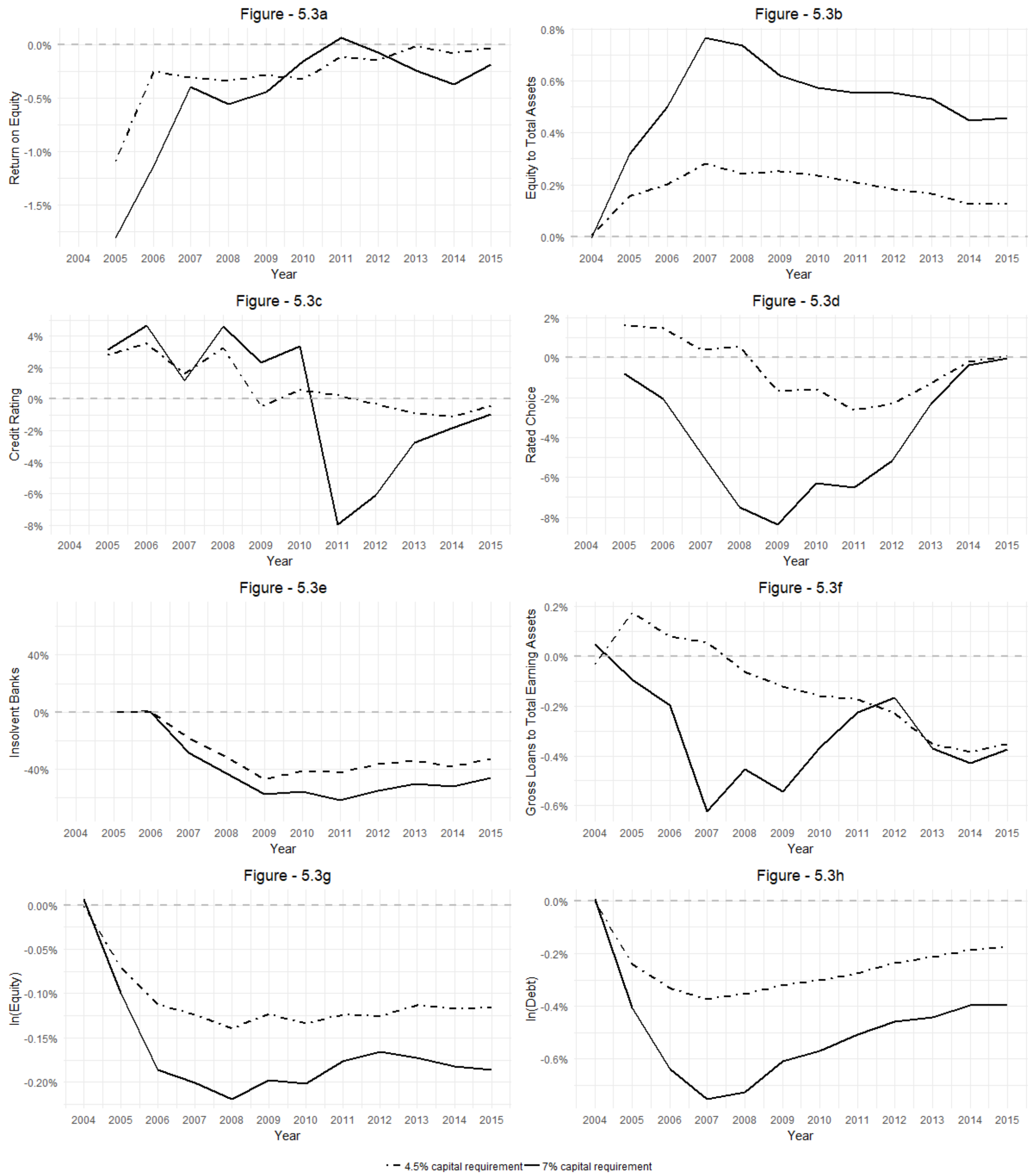
Figure 5.2: Bail in penalty



The figures show the change in the various bank characteristics and behaviour in response to a 50% (Solid Line) and 20% (Dashed Line) increase in the theoretical cost of insolvency. Figures 5.2a, 5.2b, 5.2d, and 5.2f (Return on equity, Equity to total assets, Rated Choice, and Gross loans to total earning assets) show the actual change in the value of the variable. Figures 5.2c, 5.2e, 5.2g and 5.2h (Credit rating, Insolvency, ln(Equity), ln(Debt)) show the percentage change in the variable. [189]

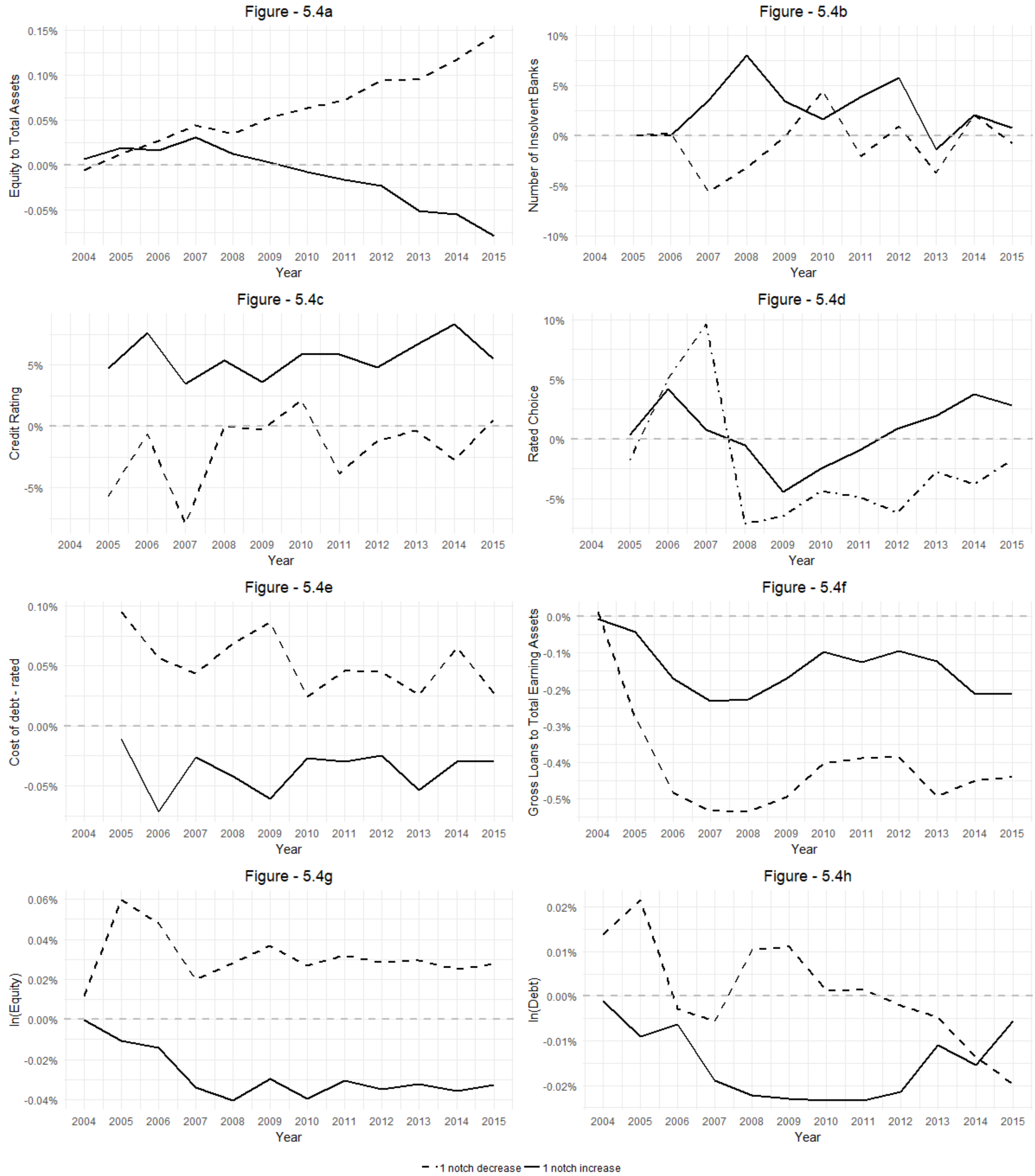
[189] The actual change in the value of the variable would be for example the ROE falling from 7% to 5%, would be a -2% change. The percentage change in the variable would be for example the credit rating falls from 13 to 12.5, would be a -3.85% change.

Figure 5.3: A change in capital requirements



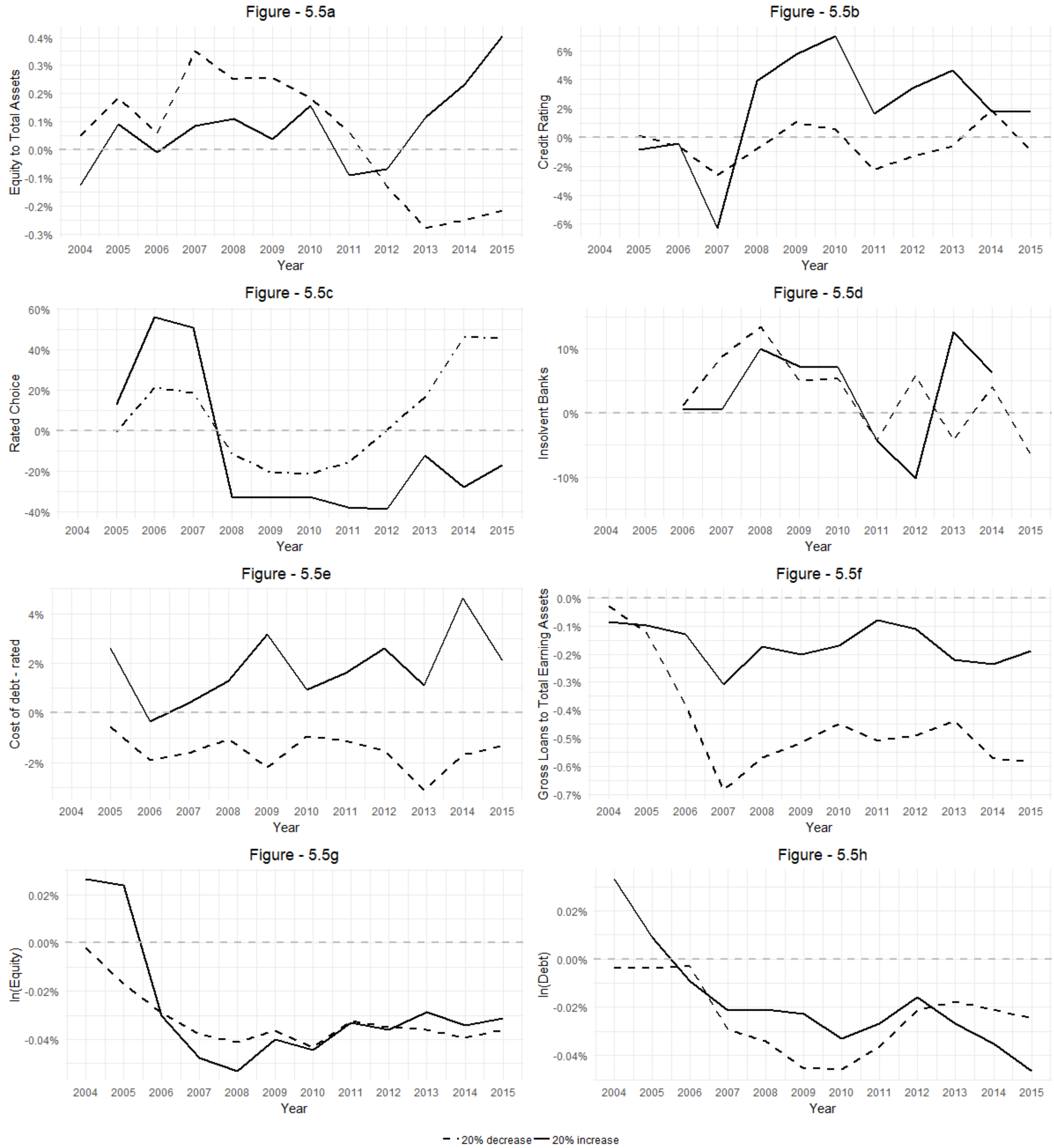
The figures show the change in the various bank characteristics and behaviour if the Basel III CET1 capital requirement of the initial 4.5% (Dashed line) and the full capital requirement of 7% (Solid Line) had been in place since 2005. Figures 5.3a, 5.3b, 5.3d, and 5.3f (Return on equity, Equity to total assets, Rated choice, and Gross loans to total earning assets) show the actual change in the value of the variable. Figures 5.3c, 5.3e, 5.3g and 5.3h (Credit rating, Insolvency, ln(Equity), ln(Debt)) show the percentage change in the variable.

Figure 5.4: A change in CRA conservatism



The figures show the change in the various bank characteristics and behaviour in response to (i) 1-notch lower ratings, i.e. an increase in rating conservatism (Dashed Line) and (ii) 1-notch higher ratings, i.e. increasingly lenient CRAs (Solid Line). Figures 5.4a, 5.4d, 5.4e, and 5.4f (Equity to total assets, Rated Choice, cost of debt and Gross loans to total earning assets) show the actual change in the value of the variable. Figures 5.4b, 5.4c, 5.4g and 5.4h (Insolvency, Credit rating, ln(Equity), ln(Debt)) show the percentage change in the variable.

Figure 5.5: Sensitivity of cost of debt to ratings



The figures show the change in the various bank characteristics and behaviour in response to (i) 1-notch lower ratings, i.e. an increase in rating conservatism (Dashed Line) and (ii) 1-notch higher ratings, i.e. increasingly lenient CRAs (Solid Line). Figures 5.5a, 5.5c, 5.5e, and 5.5f (Equity to total assets, Rated Choice, cost of debt and Gross loans to total earning assets) show the actual change in the value of the variable. Figures 5.5b, 5.5d, 5.5g and 5.5h (Credit rating, Insolvency, ln(Equity), ln(Debt)) show the percentage change in the variable.

APPENDIX 5.I – SUPPORTING TABLES

Table A. 5.1: Expenses and adjustment costs – t-test

Variable		No change	Large change	Difference	t stat
Debt	Obs	2,494	813		
	Coeff	2.619%***	3.773%***	1.154%***	9.04
Business Model	Obs	2,079	959		
	Coeff	2.654%***	2.885%***	0.231%**	2.10

*The expenses to total assets ratio (%) for banks with and without a large change in debt or business model. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

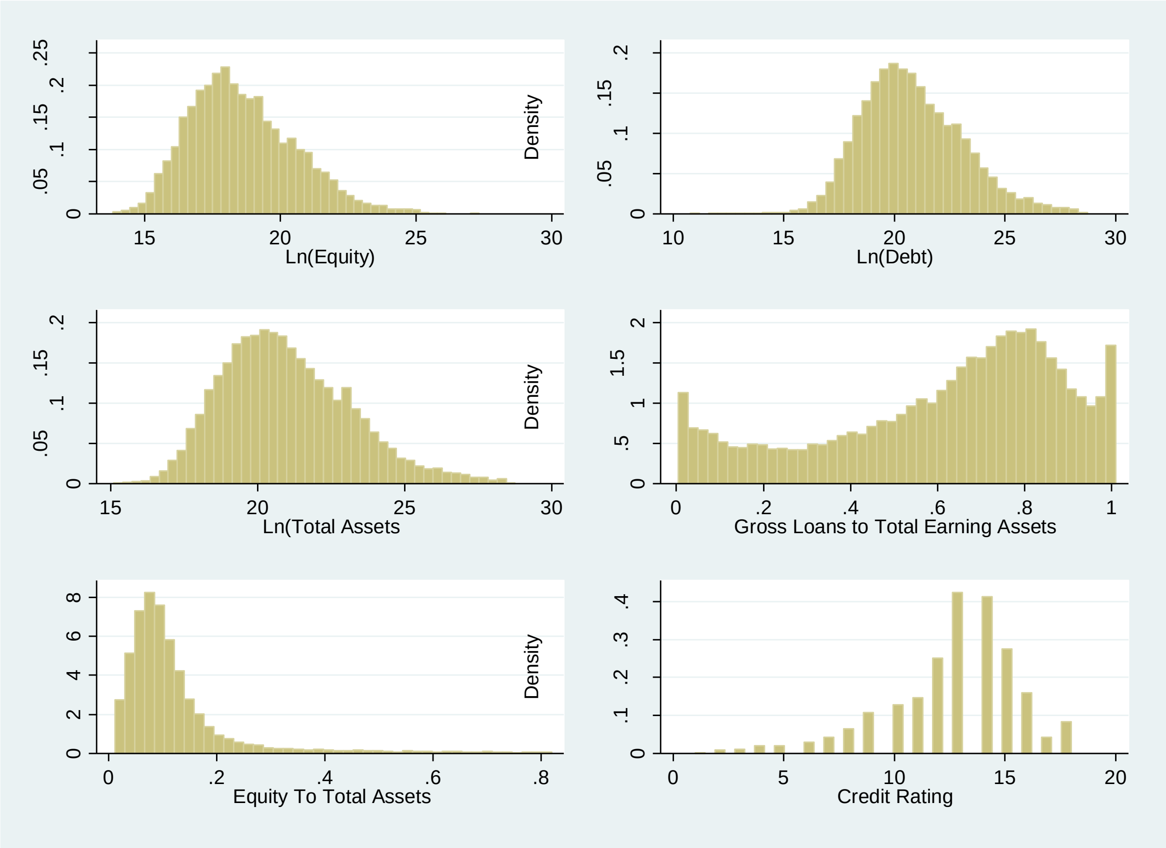
Table A. 5.2: Long term debt usage and bank size – t-test

		Bank size				
Group		Small	Medium	Large	Difference	T-Test statistic
Small vs Large	Obs	121		731		
	Coeff	0.600***		0.746***	-0.147***	-6.50
Small vs Medium	Obs	121	623			
	Coeff	0.600***	0.616***		-0.016	-0.55
Medium vs Large	Obs		623	731		
	Coeff		0.616***	0.746***	-0.131***	-9.48

*The proportion of a banks debt that is long term (>1 year and varies from 0 to 1). Standard errors in parentheses. ***, **, * represent significance beyond the 1st, 5th and 10th percentile levels respectively.*

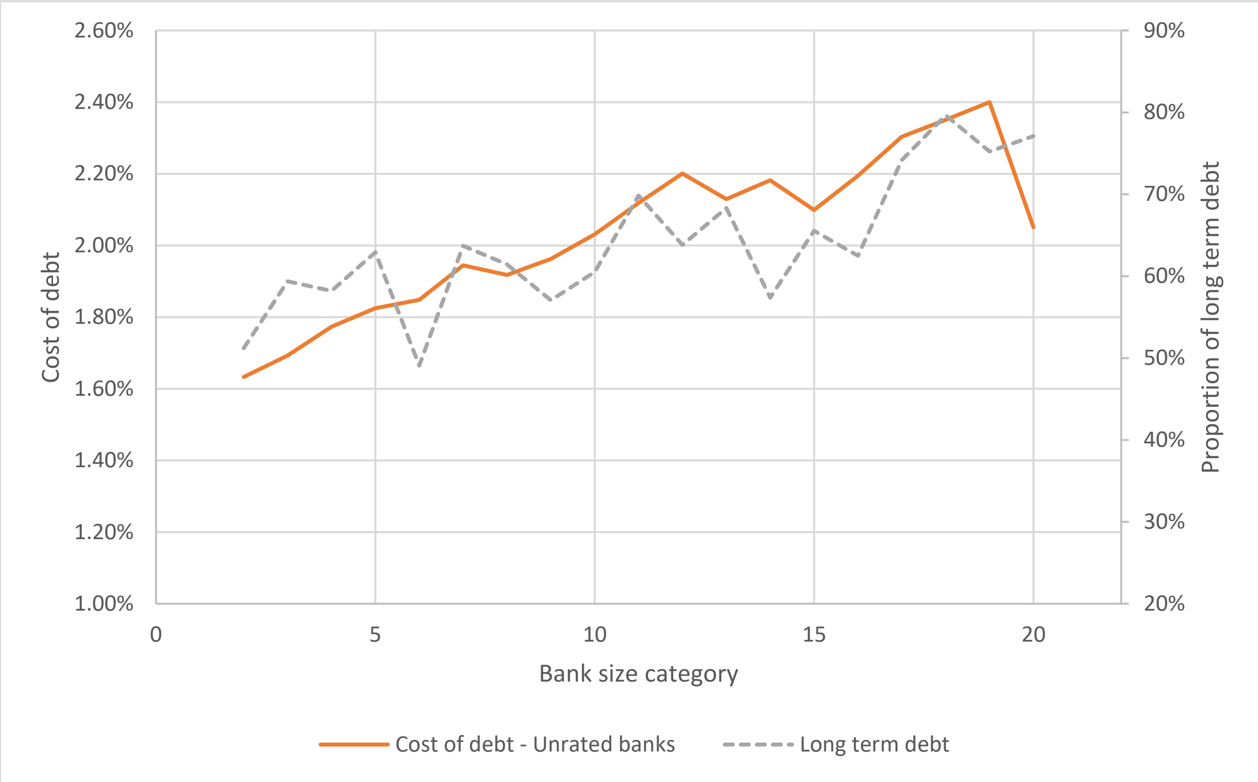
APPENDIX 5.II – SUPPORTING FIGURES

Figure A. 5.1: Key bank variable distributions



The distribution of the different banking variables in the EU sample from 2004 to 2015.

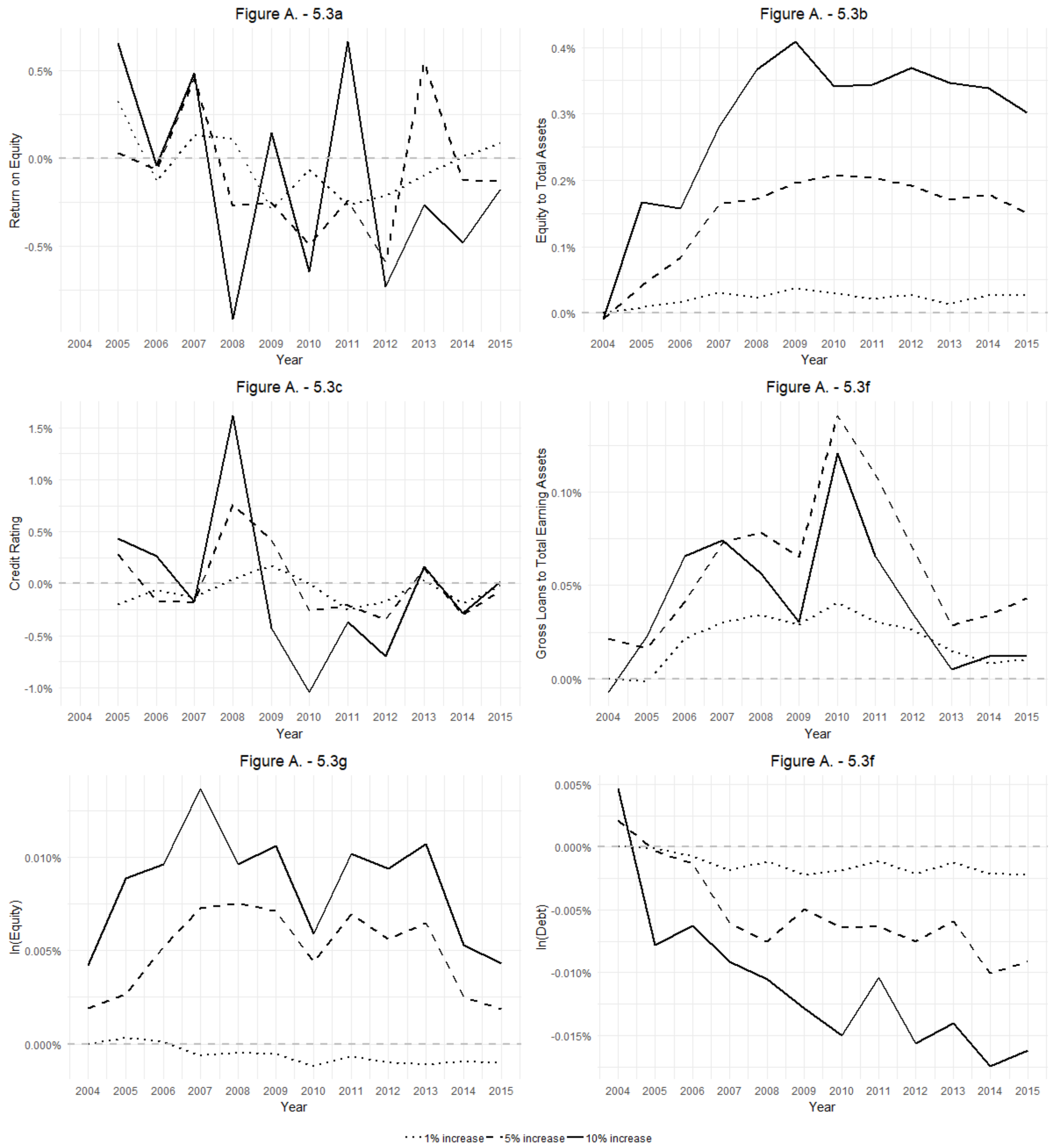
Figure A. 5.2: Relation between cost of debt, size and long-term debt usage.



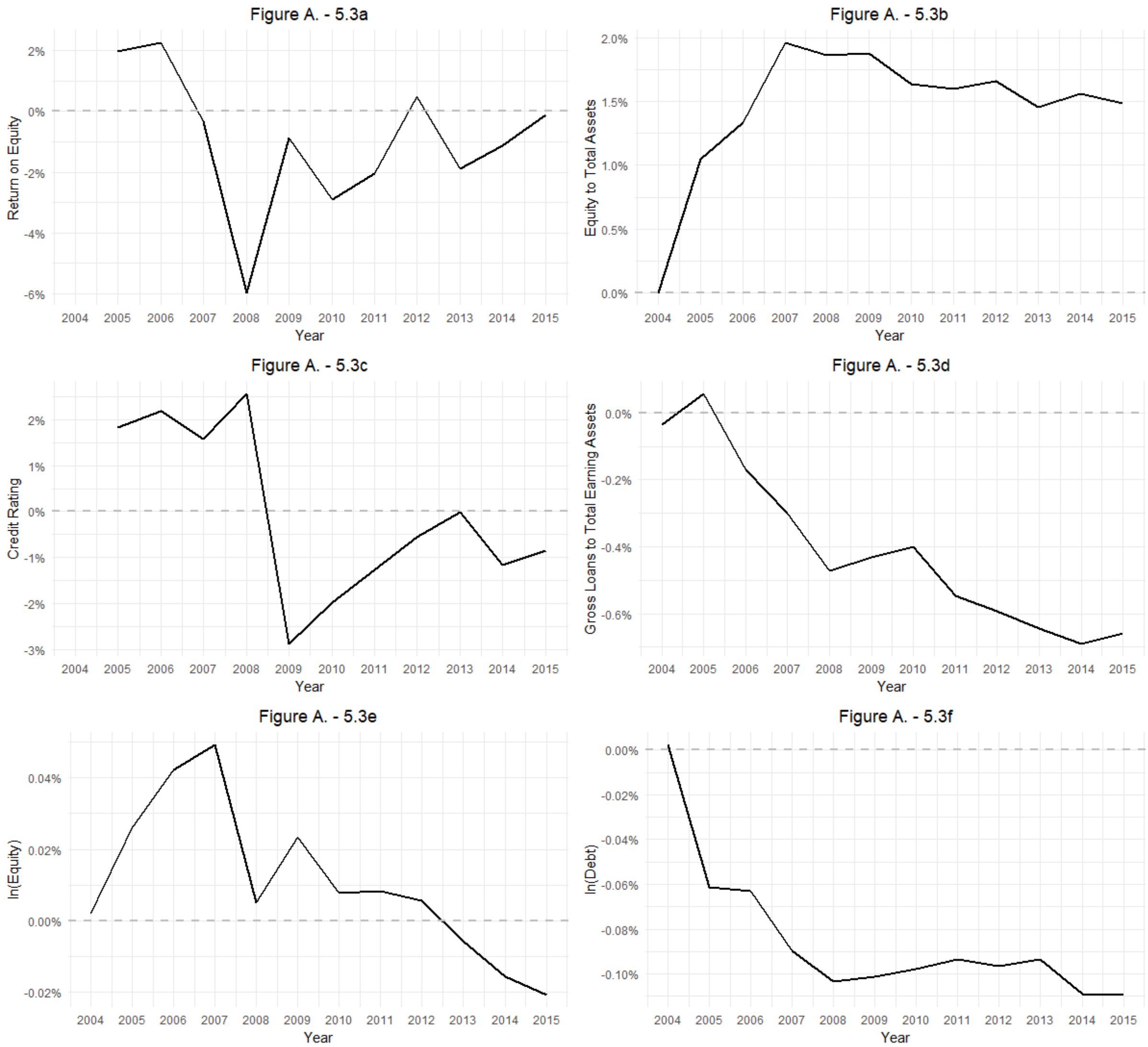
Cost of debt for unrated banks and the percentage long term debt held by their size categories (1 is the smallest, 20 is the largest).

Figure A. 5.3: Bail in penalty – additional values

Panel A: 1%, 5% and 10%

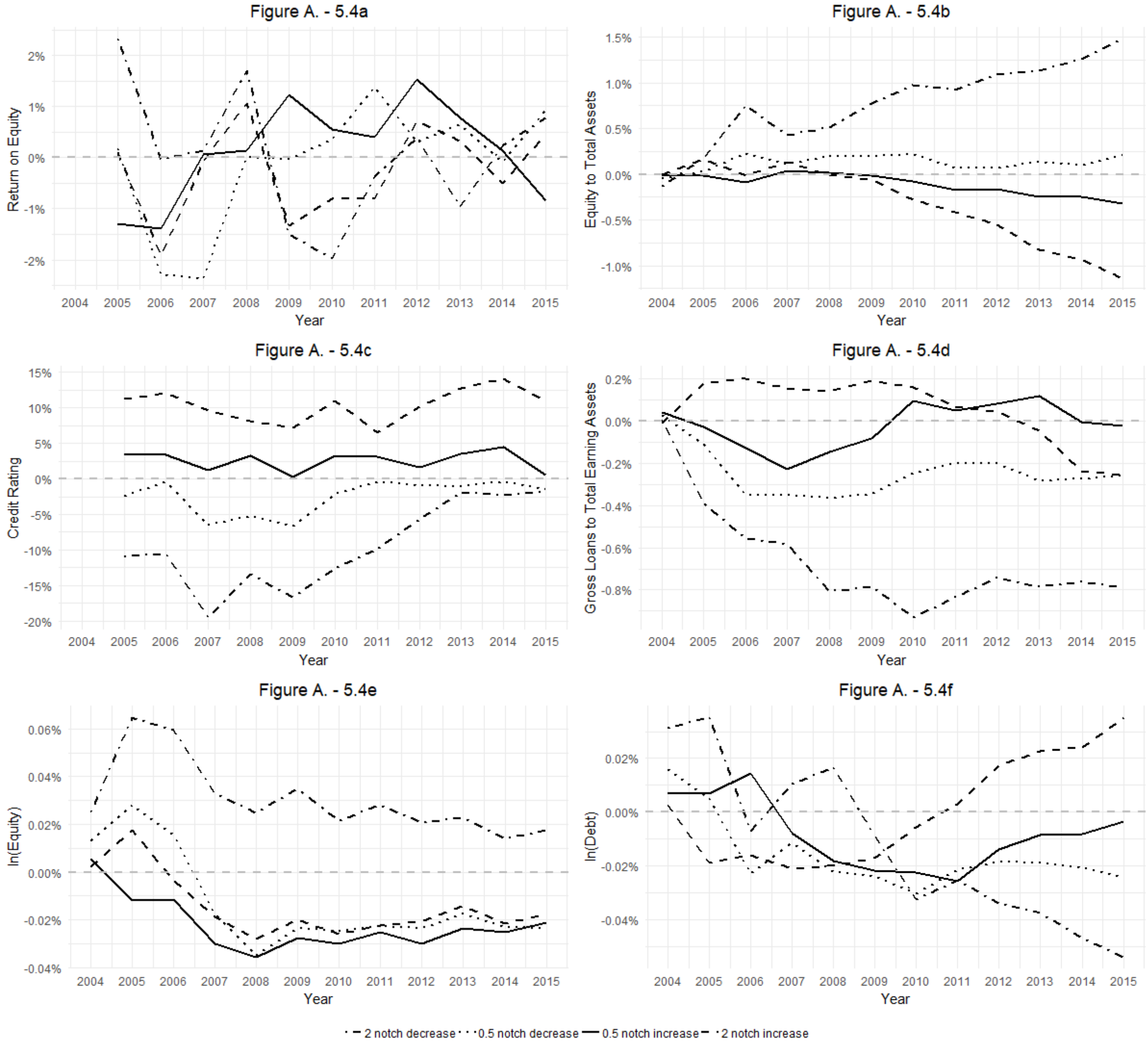


Panel B: 100%



The figures show the change in the various bank characteristics and behaviour in response to a (i) 1% (dotted line), 5% (dashed line) and 10% (solid line) increase in the theoretical cost of insolvency in Panel A and a 100% increase in Panel B. Figures A. 5.3a, 5.3b and 5.3d (ROE, Equity to total assets and Gross loans to total earning assets) show the actual change in the value of the variable. Figures A. 5.3c, 5.3e and 5.3f (Credit rating, ln(Equity), ln(Debt)) show the percentage change in the variable.

Figure A. 5.4: A change in CRA conservatism – additional values



The figures show the change in the various bank characteristics and behaviour in response to (i) 2-notch lower ratings (dot-dashed line) (ii) 0.5-notch lower ratings (dotted line), (iii) 0.5-notch higher ratings (solid line) and (iv) 2-notch higher ratings (dashed lines). Figures A. 5.4a, 5.4b and 5.4d (ROE, Equity to total assets and Gross loans to total earning assets) show the actual change in the value of the variable. Figures A. 5.4c, 5.4e and 5.4f (Credit rating, ln(Equity), ln(Debt)) show the percentage change in the variable.

Conclusion

Chapter 6

6.1 CONCLUSION

The main aim of this thesis is to investigate the effect of the recent regulatory reforms of CRAs in EU and US on the quality of FI credit ratings. The thesis also estimates a dynamic model of European FI behaviour and uses the model to simulate and examine the impact of various regulations (including the reforms of the FI rating industry, Basel III capital reforms and the Bail-in regime) on FI's performance.

The 2008 global financial crisis stimulated increased scrutiny, by regulators and the public, of the quality of the ratings issued by CRAs (see Section 2.2.10). The presence of inflated ratings misled the market about the true financial condition of many of the FIs in the run up to the crisis, with the most notable example being Lehman Brothers' AAA rating months before its financial collapse. Regulators acknowledge that high quality ratings are vital for the efficient functioning of the financial system, as credit ratings are heavily relied upon by investors and regulators.

In response to criticism of the role CRAs played the financial crisis, both EU and US regulators enacted reforms of the rating industry. These reforms seek to eliminate the presence of rating inflation and to improve rating quality, thereby providing financial markets with more informative and accurate ratings. The EU enacted CRA I in September 2009, CRA II in July 2011 and CRA III in May 2013, bringing in new rules and penalties for CRAs, establishing a new regulatory body (ESMA) and instigating a new civil liability regime respectively (see Section 2.3.2). While the US enacted the Dodd-Frank Act (DFA) in July 2010 that brought in reforms requiring the increase disclosure and monitoring of CRAs (see Section 2.3.3).

Further, failures of large financial institutions during the 2008 financial crisis exacerbated the crisis, caused significant damage in the real economy. To prevent future repeats, regulators responded with a number of new measures. In addition to regulating CRAs, notable European regulatory efforts to reform FI were evident in two distinct areas: (i) capital requirement regulations (Basel III), and (ii) European Banking Union, including a bail-in regime. The Basel III capital regulation requires FIs to hold more equity[190] (less debt) in an effort to ensure that FIs are adequately capitalised to protect against negative shocks and causes them to stand to lose more in the event of insolvency. The establishment of the bail-in regime, through the new BRRD (see Section 2.4.4), aims to shift the burden of FI failure from the taxpayers, through

[190] Now 7% common equity capital ratio, made up of a 4.5% requirement and a 2.5% capital conservation buffer.

government bail-outs, to the equity holders first and the FI' creditors second. Both of these efforts should mean that FIs stand to lose more in the event of insolvency (more "skin in the game") and consequently should reduce their risk-taking behaviour.

Chapters 3 and 4 of the thesis focus on the changing behaviour of CRAs and of FI ratings, given their pivotal role before and during the global financial crisis. FIs are much more opaque than firms in other industries, due to their complex nature, and subject to a wide range of different risks, which makes them more difficult to rate compared with firms in other industries (Flannery et al., 2013; Morgan, 2002). Also, FI ratings affect the cost of borrowing, and hence the amount of lending done by FIs and the supply of credit in the real economy. They are also key determinants of the quality of FIs' portfolios, the quality of collateral to obtain liquidity from central banks, and capital adequacy requirements. This thesis provides evidence on the changes in the quality of FI's ratings following the CRA regulatory reforms in EU and US, an aspect which is neglected in the earlier literature (see Sections 2.3.4 and 2.3.5). In addition, and to the best of my knowledge, this thesis is the first study to build and estimate a dynamic model of FI behaviour and performance. Further, understanding the effect of the regulatory reforms on both the FI rating industry and the knock-on effect on FIs themselves and their subsequent changes in behaviour is a vital topic.

The thesis investigates three key research questions. Chapter 3 address the first research question: 'What is the impact of the EU regulatory reforms on the EU FI rating sector?'. A sample of 758 rated FIs by Moody's, S&P and Fitch in 27 EU countries during the period from 1st January 2006 to 1st June 2016 is employed. The impact of the regulation on rating levels, the incidence of false warnings (unjustified downgrades) and the informational content of rating announcements are examined. Three hypotheses are proposed: *disciplining*, *conservatism* and *reputation* hypotheses (see Section 3.3). The *disciplining hypothesis* states that the regulation succeeds in the objective of increasing rating quality, on the grounds that increased legal and regulatory demands will motivate CRAs to invest in improvements to their methodologies, due diligence and performance monitoring. This should result in a warranted decrease in rating levels and an increase in rating quality. Secondly, *rating conservatism* argues that CRAs expose themselves to greater scrutiny, fines and potential liability by over-rating (less conservative) than under rating (more conservative). As a result, if scrutiny, fines and a CRAs liability for its ratings are increased, this will cause CRAs to shift to more conservative rating behaviour to avoid the increased repercussions of over rating. This will result in an unwarranted fall in rating levels and less informative rating downgrades. Lastly, *reputation* *hypothesis* states that CRAs may respond to reputational shocks and increased scrutiny, from both the regulators and the public, by lowering ratings beyond a level warranted by the FIs financial characteristics to protect and rebuild their reputation. This will result in unwarranted fall in rating levels and less informative rating downgrades, but crucially the effect differs with the strength of reputational concerns.

The results of Chapter 3 suggest that the EU regulatory reforms have been successful in reducing rating inflation and managed to significantly decrease in rating levels. However, evidence indicates that these changes are due to increased *rating conservatism* on the part of CRAs, caused by the increased regulatory scrutiny, penalties and liability. In addition to significantly lower rating levels, the results show a significant increase in false warnings (unjustified downgrades), which in turn contributes to an observed decrease in the market reactions to rating downgrades (less informative downgrades), which is consistent with increasingly conservative rating behaviour. Rating upgrades are increasingly informative, consistent with CRAs expending greater effort to ensure that each upgrade is warranted as upgrades expose CRAs to greater scrutiny. The May 2013 regulatory update strengthens the effect of the regulation, with a stronger decrease in rating levels and increase in false warnings. The evidence of *rating conservatism* in the EU FI rating market contrasts with results from the US corporate rating market where reputational concerns dominate in the post regulatory period. The EU sees a homogenous effect across regions with differing reputational concerns (see Section 3.5).

Chapter 4 examines the following research question: 'What the impact of US regulatory reforms (Dodd-Frank act (DFA)) on the FI rating industry?' A sample of 454 US FIs across all the US states rated by Moody's, S&P and Fitch during the period 1st January 2005 to 1st June 2016 is considered. As in Chapter 3, the impact of the regulation on rating levels, the incidence of false warnings and the informational content of rating announcements are examined (see Section 4.5). The study examines whether there is evidence supporting *disciplining*, *conservatism* and/or *reputation* hypotheses.

The results of Chapter 4 show no evidence supporting *rating conservatism* or *reputation hypothesis* (no increase in false warnings and no variation with reputational concerns). Yet, it appears that each CRA has responded differently to the DFA (see Section 4.5). This result contrasts both the US corporate rating market and the EU FI rating market. While S&P's FI rating levels are unaffected by the regulation, Moody's FI ratings rating levels are significantly lower and Fitch's FI rating levels are significantly higher in the post-DFA period. There is no change in the incidence of false warnings across the three CRAs. Noticeably, the US's SEC has been more cautious in enforcing the regulation than the EU's ESMA, as evident by the lack of fines in the US under the new regulatory regime. It is possible that the potential lack of rigorous enforcement has meant that CRAs are not stimulated to adopt a conservative rating approach. Possibly S&P have already been complying with many of the stricter rating standards and is hence relatively unaffected by the passage of DFA, while Moody's which are historically more conservative further this tendency, although it is warranted by subsequent outcomes. Fitch may have had a downward bias on their rating that has been subsequently removed by the passage of the DFA. There is however, consistent evidence of a dampening in market reactions to rating downgrades and upgrades for all three CRAs, indicative of the stocks markets diminishing reliance on credit ratings in the US. One potential reason for this it that passage of the regulation highlights issues with the rating industry to market participants and could cause them to take a more critical approach when considering credit rating signals. More critical participants will be less likely to react blindly, or overreact, to rating announcements.

Chapter 5 considers the following research question: 'What is the knock-on effect of recent regulatory reform on FI's behaviour and decision-making in the economy'. A dynamic model of FI behaviour and performance is estimated and then used to simulate counterfactual scenarios that examine the potential influence of pre-crisis adoption of (i) the reform of the credit rating industry, (ii) a European bail-in regime, and (iii) Basel III capital requirements. A sample of 6,121 FIs from 27 EU countries during 2004 to 2015 is employed in this Chapter.

Chapter 5 builds and estimates a dynamic model of FI behaviour and then runs four counterfactual scenarios to evaluate the impact, on FI behaviour, of both CRAs regulations and FI regulatory reforms. The results show that CRA reforms that stimulate a shift in rating practices (i.e. a shift to increasing conservative rating behaviour), cause FIs to respond by manipulating their capital ratios (increasingly conservative rating practices causes FIs to bolster their ratings by increasing capital ratios). This then impacts other areas of FI behaviour, and a systematic increase in conservative rating practices (as in the EU) will add to FIs uncertainty and they will respond by reducing their lending activities.[191] Conversely, increasingly lenient CRAs result in increased FI insolvency rates during crisis periods as FIs take advantage of the higher ratings by reducing their capital ratios. This balance between promoting FI lending and

[191] In part caused by the need to increased profits as a result of reduced leverage.

ensuring FI stability is one that regulators will have to consider. Clearly, the leniency (and inflation) that occurred during the 2008 financial crisis is not the optimum balance.

Further, additional reforms of the banking industry (Basel III capital requirements and bail-in) are considered in the model. More stringent capital requirements (4.5% and 7%) stimulate an increase in FI capital ratios, driven by a fall in debt and resulting in increased FI stability, although the effect diminishes with time in the sample. The effect of increased capital ratios on FI insolvency rates exhibits a non-linear function. FIs switch from lending activities to non-interest income to maintain profit levels (that fall due to reduced leverage) when constrained by capital requirements. This again means that regulators must find the social optimum and balance a fall in FI profits and lending capacity (which is an intrinsic part of FIs role as liquidity providers in the economy) against FI stability during crisis periods and the resultant impact of government intervention. The presence of the bail-in regime stimulates the adoption of higher optimal capital ratios as FIs have increasing “skin in the game”. This is complemented by decreased FI insolvency during crisis periods although again results in reduction in lending to maintain profit levels. While the effect from the bail-in is smaller than that of the capital requirements, it crucially results in a new equity to total assets equilibrium. This new equilibrium is due to a shift in, rather than simply constraining, FI behaviour. The increased insolvency costs rebalance FIs priorities when considering the sum of future profits and the potential of insolvency.

The thesis provides insights into four important and previously unexplored areas. Firstly, Chapter 3 shows that the EU regulatory reforms (CRA I, II and III) of the FI rating sector acted through a previously unexplored and unconsidered channel, that of increased *rating conservatism* stimulated by the regulation. Secondly, Chapter 4 demonstrates that effect of US regulatory reforms of the FI rating industry (DFA) contrast with evidence from both the EU FI rating industry (*rating conservatism*) and the US corporate rating industry (*reputation hypothesis*). The results indicate that the regulation is relatively ineffective at providing a consistent industry wide effect, most likely caused by the lack of effective enforcement by the SEC. Rather, each CRA is interpreting and reacting to the regulation in a different manner. Thirdly, Chapter 5 implements and estimates for the first time a dynamic model of FI behaviour and is the first time a DCDP model is applied to the banking sector. Lastly, Chapter 5 provides insights into how the recent EU FI rating industry reforms have impacted FI behaviour. The results reveal the previously unexplored link between the rating regulatory reforms and FI behaviour and demonstrate that FIs compensate for changes in rating practices by varying their capital ratios, lending practices and debt levels. Additionally, recent FI reforms (Basel III capital requirements and EU Bail-in regulation) are shown to be effective at promoting FI stability during crisis periods but comes at the cost of a reduction in lending (liquidity provision). The results emphasise the need for regulators to carefully manage the trade-off between minimizing FI risk and promoting lending.

One of the principle implications for EU regulators is that they must beware that the increased penalties, liability and scrutiny placed on CRAs do not exacerbate the conservative rating bias within the FI rating industry, as this bias is making rating downgrades less informative. They must seek ways to promote increased rating quality through further methodological reforms and ensure due diligence. Regulators should also be careful when implementing increased-competition measures, like in the structured ratings market, as there is evidence that increased competition among CRAs leads to more inflated FI ratings. A more significant reform such as establishing a centralised system where ratings are delegated to CRAs could potentially remove some of the conflicts of interest inherent in the issuer pays model, e.g. ratings shopping, inflation and competition. An additional consideration of increasingly conservative FI rating that EU regulators should be aware of, is the potential to reduce FI lending (and loan making activities, see Section 5.6.3).[192] The positive effect of lower ratings is that it causes FIs to bolster capital levels and can results in strengthened FI stability during crisis periods, hence regulators should deter increased rating leniency.

The empirical results from simulations of the effect of the bail-in and capital requirements on FI behaviour emphasise the importance of understanding the interactions between regulatory changes and the dynamics of FI's decision making and risk taking. The results support the argument that the implementation of the bail-in and capital requirement would have a positive impact by reducing FI insolvency rates, in particular during crisis periods, and lessening the burden on governments. Regulators should balance the reduction in insolvency rates (which exhibit a non-liner function) against the fall in FI sizes and profits. The findings imply a potentially effective method of mitigating FIs' risk-taking by combining increased capital requirements with the introduction of a bail-in regime. The increased responsibility of equity holders for losses complements the increased "skin in the game" caused by greater levels of capital and is necessary to ensure a shift to a reduced risk-taking equilibrium.

[192] Lower ratings cause FIs to increase their capital ratios, they then reduce lending (and move to non-interest activities) to combat the fall in profits from lower leverage.

In the US, regulators should examine why the effect of the regulation is different across CRAs and should question whether they have gone far enough as the regulation is having no net impact other than decreasing rating informativeness. They should first question whether the regulation is being effectively implemented as CRAs do not appear to be reacting in a conservative manner. Secondly, they should investigate what precisely is driving the reduced market reactions to rating announcements.

While this thesis limits itself to examining the FI rating industries, the regulatory reforms in the EU and US also encompass the corporate rating industries. While there has been some research on the US reforms (e.g. Dimitrov et al., 2015), little is known about the impact of the reforms on the EU corporate ratings market. There is potential for further investigation to see if, similar to the FI rating market, the effect of the regulatory reforms differs between the two regions.

Another limitation is the way in which the dynamic model is constructed. Due to the limitations of the technique, the model cannot be all encompassing and therefore the model must be restricted to examining the key areas of focus. One aspect that was not included is the precise mechanism of the bail-in, this was approximated in the model, but further research could consider an alternative model specification that would enable the examination of the specific mechanism used in the bail-in and how variations in this mechanism can impact FI behaviour. An additional area of interest is expanding the model to consider how FIs respond to deposit shocks and to the potential of bank runs.

Due to time limitation, the dynamic model was only applied to the EU dataset, a potential avenue of future research lies in applying dynamic structural estimation to modelling FI behaviour in US. It is possible that they will behave differently during the period as the US was not affected as heavily by the EU sovereign debt crisis that caused many of the EU FIs to be downgraded due to the transmission of risk through the sovereign-bank ratings channel.

References

Abedifar, P., Molyneux, P. Tarazi, A. (2018). Non-interest income and bank lending. Journal of Banking and Finance, 87, 411-426.

Acharya, V. V., Drechsler, I., Schnabl, P. (2014). A Pyrrhic victory? Bank bailouts and sovereign credit risk. Journal of Finance, 69(6), 2689–2739.

Acharya, V. V., Mora, N. (2015). A crisis of banks as liquidity providers. Journal of Finance, 70(1), 1–43.

Acharya, V. V., Schnabl, P., Suarez, G. (2013). Securitization without risk transfer. Journal of Financial Economics, 107, 515–536.

Admati, A. R., DeMarz, P. M., Hellwig, M. F., Pfleiderer, P. (2013). Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not socially expensive. Working Paper, Stanford Graduate School of Business, 2011.

Admati, A., and Hellwig, M. (2013). The Bankers New Clothes. Princeton, NJ: Princeton University Press.

Afonso, A, Gomes, P., Rother, P. (2011). Short- and long-run determinants of sovereign debt credit ratings. International Journal of Finance and Economics, 16, 1–15.

Afonso, A., Furceri, D., Gomes, P. (2012). Sovereign credit ratings and financial markets linkages: Application to European data. Journal of International Money and Finance, 31, 606–638.

Alcubilla, R. G., Del Pozo, J. R. (2012) Credit rating agencies on the watch list: Analysis of European regulation. New York: Oxford University Press.

Allen, F., Carletti, E., Marquez, R. (2015). Deposits and bank capital structure. Journal of Financial Economics, 118, 601–619.

Almeida, H., Cunha, I., Ferreira, M. A., Restrepo, F. (2017). The real effects of credit ratings: The sovereign ceiling channel. Journal of Finance, 72, 249-290.

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

Alsakka, R, ap Owain, G. (2013). Rating agencies' signals during the European sovereign debt crisis: Market impact and spillovers. Journal of Economic Behavior and Organization, 85, 144–162.

Alsakka, R., ap Gwilym, O., Klusak, P., Tran, V. (2015). Market impact under a new regulatory regime: Credit rating agencies in Europe. Economic Notes, 44(2), 275–307.

Alsakka, R., ap Gwilym, O., Vu, H. (2017). Differences of opinion in sovereign credit signals during the European crisis. European Journal of Finance Forthcoming, 0–38.

Alsakka, R., ap Gwilym, O., Vu, T. N. (2014). The sovereign-bank rating channel and rating agencies' downgrades during the European debt crisis. Journal of International Money and Finance, 49, 235–257.

Altunbas, Y, Marqués-Ibáñez, D., Manganelli. S. (2017). Realized bank risk during the great recession. Journal of Financial Intermediation, 32, 29-44.

Altunbas, Y., Gambacorta, L., Marqués-Ibáñez, D. (2014). Does monetary policy affect bank risk-taking? International Journal of Central Banking, 10(1).

Ashcraft, A. B., Schuermann, T. (2008). Understanding the securitization of subprime mortgage credit. Staff Report, Federal Reserve Bank of New York, No. 318.

Attaoui, S., Poncet, P. (2015). Write-down bonds and capital and debt structures. Journal of Corporate Finance. 35, 97–119.

Ayadi, R., De Groen, W. P. (2014). Banking business models monitor 2014: Europe. Centre for European Policy Studies and International Observatory on Financial Services Cooperatives paper, 1–70.

Ayadi, R., Thyri, P. (2015). State aid to banks and credit for SMES: Is there a need for conditionality? Economic and Monetatry Affairs, European Parliament.

Bae, K.-H., Kang, J.-K., Wang, J. (2015). Does increased competition affect credit ratings? A reexamination of the effect of Fitch's market share on credit ratings in the corporate bond market. Journal of Financial and Quantitative Analysis, 50(05), 1011–1035.

Baghai, R. P., Servaes, H., Tamayo, A. (2014). Have rating agencies become more conservative? Implications for capital structure and debt pricing. Journal of Finance, 69, 1961–2005.

Bai, L. (2010). The performance disclosures of credit rating agencies: Are they effective reputational sanctions? New York University Journal of Law and Business, 11.

Baker, M., Wurgler, J. (2015). Do strict capital requirements raise the cost of capital? Bank regulation, capital structure, and the low-risk anomaly. American Economic Review, 105, 315–320.

Bakke, T., Gu, T. (2017). Diversification and cash dynamics. Journal of Financial Economics, 123, 580–601.

Bannier, C. E., Behr, P., Güttler, A. (2010). Rating opaque borrowers: Why are unsolicited ratings lower? Review of Finance, 14(2), 263–294.

Bar-Isaac, H., Shapiro, J. (2013). Ratings quality over the business cycle. Journal of Financial Economics, 108(1), 62–78.

Bazerman, M. H., Loewenstein, G., Moore, D. A. (2002). Why good accountants do bad audits. Harvard Business Review, 80, 96–102, 134.

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

Bedendo, M., Cathcart, L., El-Jahel, L. (2018). Reputational shocks and the information content of credit ratings. Journal of Financial Stability, 34, 0–32.

Behr, P., Güttler, A. (2008). The informational content of unsolicited ratings. Journal of Banking and Finance, 32(4), 587–599.

Behr, P., Kisgen, D. J., Taillard, J. P. (2018). Did government regulations lead to inflated credit ratings? Management Science, 64(3), 1034–1054.

Benhabib, J., Miao, J., Wang, P. (2016). Chaotic banking crises and regulations. Economic Theory, 61, 393–422.

Berger, A. N., Bouwman, C. H. S. (2013). How does capital affect bank performance during financial crises? Journal of Financial Economics, 109, 146–176.

Berger, A. N., Himmelberg, C. P., Roman, R. A., Tsyplakov, S. (2018). Bank bailouts, bail-ins, or bankruptcy? A dynamic model and empirical tests of optimal regulatory design. Working Paper.

Bethel, J. E., Ferrell, A., Hu, G. (2008). Legal and economic issues in litigation arising from the 2007-2008 credit crisis. Harvard Law and Economics Discussion Paper, 163–235.

Betz, F., Oprică, S., Peltonen, T. A., Sarlin, P. (2014). Predicting distress in European banks. Journal of Banking and Finance, 45, 225–241.

Bhagat, S., Bolton, B. (2014). Financial crisis and bank executive incentive compensation. Journal of Corporate Finance, 25, 313–341.

Bloomberg (2013). Egan-Jones Banned for 18 Months From Rating Sovereigns, http://www.bloomberg.com/news/articles/2013-01-22/egan-jones-faces-18-month-ban-on-sovereign-asset-backed-ratings, accessed on 28/11/2018.

Blum, J. M. (2008). Why “Basel II” may need a leverage ratio restriction. Journal of Banking and Finance, 32(8), 1699–1707.

Bolton, P., Freixas, X., Shapiro, J. (2012). The credit ratings game. Journal of Finance, 67(1), 85–111.

Bongaerts, D. (2014). Alternatives for issuer-paid credit rating agencies. ECB Working Paper No. 1703.

Bongaerts, D., Martijn Cremers, K. J., Goetzmann, W. N. (2012). Tiebreaker: Certification and multiple credit ratings. Journal of Finance, 67, 113–152.

Boylan, S. J. (2008). A classroom exercise on unconscious bias in financial reporting and auditing. Issues in Accounting Education, 23, 229–245.

Boylan, S. J. (2012). Will credit rating agency reforms be effective? Journal of Financial Regulation and Compliance, 20(4), 356–366.

Brighi, P., Venturelli, V. (2014). How do income diversification, firm size and capital ratio affect performance? Evidence for bank holding companies. Applied Financial Economics, 3107, 1–18.

Byoun, S. (2014). Information content of unsolicited credit ratings and incentives of rating agencies: A theory. International Review of Economics and Finance, 33, 338–349.

Byoun, S., Fulkerson, J. A., Han, S. H., Shin, Y. S. (2014). Are unsolicited ratings biased? Evidence from long-run stock performance. Journal of Banking and Finance 42, 326–338.

Byoun, S., Shin, Y. S. (2012). Information content of unsolicited credit ratings: Evidence from Japanese firms. Asia-Pacific Journal of Financial Studies, 41, 59–86.

Calem, P., Rob R. (1999). The impact of capital-based regulation on bank risk-taking. Journal of Financial Intermediation, 8, 317–352.

Camanho, N., Deb, P., Liu, Z. (2010). Credit Rating and Competition. LSE Financial Markets Group Discussion Paper Series.

Cantor, R., Packer, F. (1997). Differences of opinion and selection bias in the credit rating industry. Journal of Banking and Finance, 21, 1395–1417.

Caporale, G. M., Matousek, R., Stewart, C. (2012). Ratings assignments: Lessons from international banks. Journal of International Money and Finance, 31(6), 1593–1606.

Chen, S. S., Chen, H. Y., Chang, C. C., Yang, S. L. (2016). The relation between sovereign credit rating revisions and economic growth. Journal of Banking and Finance, 64, 90–100.

Christopher, R., Kim, S. J., Wu, E. (2012). Do sovereign credit ratings influence regional stock and bond market interdependencies in emerging countries? Journal of International Financial Markets, Institutions and Money, 22, 1070–1089.

Coffee, J. C. J. (2006). Gatekeepers: The professions and corporate governance. New York: Oxford University Press.

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

Cohen, B. H., Scatigna, M. (2016). Banks and capital requirements: Channels of adjustment. Journal of Banking and Finance, 69, 1–14.

Conlon, T., Cotter, J. (2014). Anatomy of a bail-in. Journal of Financial Stability, 15(2014), 257–263.

Consumer Bankruptcy News (2008). Credit rating agencies reach agreement with New York AG. Consumer Bankruptcy News.

Cooley T. F., Quadrini, V. (2001). Financial markets and firm dynamics. American Economic Review, 91(5), 1286–1310.

Cooper, R., Ejarque, J. (2003). Financial frictions and investment: Requiem in Q. Review of Economic Dynamics, 6(4), 710–728.

Correa, R., Lee, K. H., Sapriza, H., Suarez, G. A. (2014). Sovereign credit risk, banks' government support, and bank stock returns around the world. Journal of Money, Credit and Banking, 46, 93–121.

Cuoco, D., Liu, H. (2006). An analysis of VaR-based capital requirements. Journal of Financial Intermediation, 15(3), 362–394.

Custódio, C., Ferreira, M. A., Laureano, L. (2013). Why are US firms using more short-term debt? Journal of Financial Economics, 108, 182–212.

Dam, L., Koetter, M. (2012). Bank bailouts and moral hazard: Evidence from Germany. Review of Financial Studies, 25(8), 2343–2380.

Dang, T. V., Felgenhauer, M. (2012). Information provision in over-the-counter markets. Journal of Financial Intermediation, 21(1), 79–96.

De Nicolò, G., Gamba, A., Lucchetta, M. (2014). Microprudential regulation in a dynamic model of banking. Review of Financial Studies, 27, 2097–2138.

DeAngelo, H., and Stulz, R. M. (2015). Liquid-claim production, risk management, and bank capital structure: Why high leverage is optimal for banks. Journal of Financial Economics, 116, 219–236.

DeAngelo, H., DeAngelo, L., Whited, T. M. (2011). Capital structure dynamics and transitory debt. Journal of Financial Economics, 99, 235–261.

Deb, P., Murphy, G. (2010). Credit rating agencies: An alternative model. FMG Discussion Papers, Financial Markets Group.

Demirgüç-Kunt, A., Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. Journal of Financial Economics, 98, 626–650.

DeYoung, R., Gron, A., Torna, G., Winton, A. (2015). Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. Journal of Finance, 70, 2451–2488.

DeYoung, R., Kowalik, M., Reidhill, J. (2013). A theory of failed bank resolution: Technological change and political economics. Journal of Financial Stability, 9, 612–627.

Diamond, D. W., and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. Journal of Political Economy, 91, 401–419.

Diamond, D. W., Rajan, R. G. (2001). Liquidity risk, liquidity creation and financial fragility: A theory of banking. Journal of Political Economy, 109, 287–327.

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

Dickens, R. N., Casey, K. M., Newman, J. A. (2002). Bank dividend policy: Explanatory factors. Quarterly Journal of Business and Economics, 41, 3–12.

Dilly, M., Mählmann, T. (2016). Is there a boom bias in agency ratings? Review of Finance, 20(3), 979–1011.

Dimitrov, V., Palia, D., Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. Journal of Financial Economics, 115(3), 505–520.

Dittrich, F. (2007). The credit rating industry: Competition and regulation. Doctoral dissertation, Universität zu Köln

Doucouliagos, H., Haman, J., Askary, S. (2007). Directors' remuneration and performance in the Australian banking sector. Corporate Governance: An International Review, 15(6), 1363–1384.

Duan, J. C., Van Laere, E. (2012). A public good approach to credit ratings - From concept to reality. Journal of Banking and Finance, 36(12), 3239–3247.

EC (2014). Economic review of the financial regulation agenda. Commission Staff Working Document 2014/158, 1-344.

EC (2016). Study on the state of the credit rating market - Final report. MARKT/2014/257/F4/ST/OP

Edwards, A. K., Harris, L. E., Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. Journal of Finance, 62, 1421–1451.

Egan-Jones (2002). Letter submitted to the SEC by Egan-Jones. available at http://www.sec.gov/news/extra/credrate/eganjones2.htm, accessed on 28/11/2018

Eijffinger, S. C. W. (2012). Rating agencies: Role and influence of their sovereign credit risk assessment in the eurozone. Journal of Common Market Studies, 50, 912–921.

Ellul, A., Jotikasthira, C., Lundblad, C. T. (2011). Regulatory pressure and fire sales in the corporate bond market. Journal of Financial Economics, 101, 596–620.

Elton, E. J., Gruber, M. J., Agrawal, D., Mann, C. (2001). Explaining the rate spread on corporate bonds. Journal of Finance, 56, 247–277.

ESMA (2013). Credit rating agencies: sovereign ratings investigation. ESMA/2013/1775, European Securities and Markets Authority, Paris, France.

ESMA (2014). Credit rating agencies - Annual report 2013, ESMA/2014/151, European Securities and Markets Authority, Paris, France.

ESMA (2015a). Discussion Paper - On the validation and review of Credit Rating Agencies' methodologies. ESMA/2015/1735, European Securities and Markets Authority, Paris, France.

ESMA (2015b). Press Release: ESMA sees progress in reform of EU credit rating industry. ESMA/2015/1483, European Securities and Markets Authority, Paris, France.

ESMA (2017a). Guidelines on the validation and review of Credit Rating Agencies' methodologies. ESMA/2016/1575, European Securities and Markets Authority, Paris, France.

ESMA (2017b). Report on CRA Market Share Calculation ESMA. ESMA33-5-209, European Securities and Markets Authority, Paris, France.

Faure-Grimaud, A., Peyrache, E., Quesada, L. (2009). The ownership of ratings, RAND Journal of Economics, 40, 234–257.

Financial Stability Forum (2008). Report of the financial stability forum on enhancing market and institutional resilience.

Flannery, M. J., Kwan, S. H., Nimalendran, M. (2013). The 2007-2009 financial crisis and bank opaqueness. Journal of Financial Intermediation, 22(1), 55–84.

Flynn, S., Ghent, A. (2017). Competition and credit ratings after the fall. Management Science, 64(4), 1672–1692.

Fulghieri, P., Strobl, G., Xia, H. (2013). The economics of solicited and unsolicited credit ratings, Review of Financial Studies, 27, 484–518.

Furlong, F. T., Keeley, M. C. (1989). Capital regulation and bank risk-taking: A note. Journal of Banking and Finance, 13(6), 883–891.

Gamba, A., Triantis, A. (2008). The value of financial flexibility. Journal of Finance, 63(5), 2263–2296.

Gennaioli, N., Shleifer, A., Vishny, R. W. (2013). A model of shadow banking. Journal of Finance, 68, 1331–1363.

Goel, A. M, Thakor, A. V. (2011). Credit ratings and litigation risk. Washington University Working Paper.

Gomes, J. F. (2001). Financing investment. American Economic Review, 91, 1263–1285.

Gonzalez-Hermosillo, B. (1999). Determinants of ex-ante banking system distress: A macro-micro empirical exploration of some recent episodes. IMF Working Paper 99/33.

Gorton, G. B. (2010). Slapped by the invisible hand: The panic of 2007. New York: Oxford University Press.

Gorton, G., Pennacchi, G. (1990). Financial intermediaries and liquidity creation. The Journal of Finance, 45, 49–71.

Gouriéroux, C., Monfort, A. (1996). Simulation based econometric methods. New York: Oxford University Press, USA.

Graham, J. R., Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. Journal of Financial Economics, 60, 187–243.

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

Haan, J., Poghosyan, T. (2012). Size and earnings volatility of US bank holding companies. Journal of Banking and Finance, 36, 3008–3016.

Han, S. H., Moore, W. T., Shin, Y. S., Yi, S. (2013). Unsolicited versus solicited: Credit ratings and bond yields. Journal of Financial Services Research, 43, 293–319.

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

Hanson, S. G., Shleifer, A., Stein, J. C., Vishny, R. W. (2015). Banks as patient fixed-income investors. Journal of Financial Economics, 117, 449–469.

Hau, H., Langfield, S., Marques-Ibanez, D. (2013). Bank ratings: What determines their quality? Economic Policy, 28, 289–333.

Hayre, L. (2002). Salomon Smith Barney guide to mortgage-backed and asset-backed securities. New York: John Wiley and Sons.

He, J. J., Qian, J. Q., Strahan, P. E. (2012). Are All Ratings Created Equal? The impact of issuer size on the pricing of mortgage-backed securities. Journal of Finance, 67, 2097–2137.

Hennessy, C. A., Whited, T. M. (2005). Debt dynamics. Journal of Finance, 60, 1129–1165.

Hennessy, C. A., Whited, T. M. (2007). How costly is external financing? Evidence from a structural estimation. Journal of Finance, 62, 1705–1745.

Henriques, R. (2011). The great bank downgrade: What bail-in regimes mean for senior ratings? JP Morgan Chase Europe Credit Research.

Henry, T. R., Kisgen, D. J., Wu, J. J. (2015). Equity short selling and bond rating downgrades. Journal of Financial Intermediation, 24(1), 89–111.

Heuvel, S. V. D. (2008). The welfare cost of bank capital requirements. Journal of Monetary Economics, 55, 298–320.

Hill, P., Brooks, R., Faff. R. (2010). Variations in sovereign credit quality assessments across rating agencies. Journal of Banking and Finance, 34, 1327–1343.

Hill, P., Faff, R. (2010). The market impact of relative agency activity in the sovereign ratings market. Journal of Business Finance and Accounting, 37(9–10), 1309–1347.

Hilscher, J., Raviv, A. (2014). Bank stability and market discipline: The effect of contingent capital on risk taking and default probability. Journal of Corporate Finance, 29, 542–560.

Holmström, B., Tirole, J. (1998). Private and Public Supply of Liquidity. Journal of Political Economy, 106, 1–40.

Holmström, B., Tirole, J. (2011). Inside and outside liquidity. Massachusetts: The MIT press.

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

Horner, J. (2002). Reputation and competition. American Economic Review, 92, 644–663.

Huang, Y. L., Shen, C. H. (2015). The sovereign effect on bank credit ratings. Journal of Financial Services Research, 47(3), 341–379.

Hunt, J. P. (2009). Credit rating agencies and the "Worldwide Credit Crisis": The limits of reputation, the insufficiency of reform, and a proposal for improvement. Columbia Business Law Review 2009, 1-109.

Hüser, A. C., Hałaj, G., Kok, C., Perales, C., Kraaij, A. V. D. (2018). The systemic implications of bail-in: A multi-layered network approach. Journal of Financial Stability, 81–97.

Iannotta, G. (2006). Testing for opaqueness in the European banking industry: Evidence from bond credit ratings. Journal of Financial Services Research, 30(3), 287–309.

Imbierowicz, B., Rauch, C. (2014). The relationship between liquidity risk and credit risk in banks. Journal of Banking and Finance, 40(1), 242–256.

IMF (2010). Resolving the Crisis Legacy and Meeting New Challenges to Financial Stability. IMF Global Financial Stability Report: Meeting new Challenges to Stability and Building a Safer System (April).

IOSCO (2008). The role of credit rating agencies in structured finance markets - Final report. International Organization.

Ismailescu, I., Kazemi, H. (2009). The reaction of emerging market credit default swap spreads to sovereign credit rating changes. Journal of Banking and Finance, 34, 1–47.

Jankowitsch, R., Ottonello, G., Subrahmanyam, M. G. (2016). The new rules of the rating game: Market perception of corporate ratings. Vienna University of Economics and Business Working Papaer, 44.

Jiménez, G., Ongena, S., Peydró, J. L., Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. American Economic Review, 102(5), 2301–2326.

Johnson, R. (2004). Rating agency actions around the investment-grade boundary. The Journal of Fixed Income, 13, 25–37.

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

Kahneman, D, Tversky, A. (1982). Judgements of and by representativeness. Cambridge: Cambridge University Press.

Keane, M. P., Sauer, R. M. (2009). Classification error in dynamic discrete choice models: Implications for female labor supply behavior. Econometrica, 77(3), 975–991.

Keane, M. P., Wolpin, K. I. (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence. Review of Economics and Statistics, 76(4), 648–672.

Keane, M. P., Wolpin, K. I. (2000). Eliminating race differences in school attainment and labor market success. Journal of Labor Economics, 18(4), 614–652.

Keane, M. P., Wolpin, K. I. (2009). Empirical applications of discrete choice dynamic programming models. Review of Economic Dynamics, 12(1), 1–22.

Keane, M. P., Wolpin, K. I. (2010). The role of labor and marriage markets, preference heterogeneity, and the welfare system in the life cycle decisions of black, hispanic, and white women. International Economic Review, 51(3), 851–892.

Keeley, M. C., Furlong, F. T. (1990). A re-examination of mean-variance analysis of bank capital regulation. Journal of Banking and Finance, 14, 69–84.

Kerlin, J., Malinowska-Misiąg, E., Smaga, P., Witkowski, B., Nowak, A. K., Kozłowska, A., Wiśniewski, P. (2016). European bank restructuring during the global financial crisis. Basingstoke: Palgrave Macmillan.

Kisgen, D. J. (2006). Credit Ratings and Capital Structure. Journal of Finance, 61(3), 1035–1072.

Kisgen, D. J. (2007). The influence of credit ratings on corporate capital structure decisions. Journal of Applied Corporate Finance, 19, 65–73.

Kisgen, D. J. (2009). Do firms target credit ratings or leverage levels? Journal of Financial and Quantitative Analysis, 44, 1323–1344.

Kisgen, D. J. (2012). The real and financial effects of credit ratings: Evidence from Moody's adjustments. Working paper, 1–40.

Kisgen, D. J., Strahan, P. E. (2010). Do regulations based on credit ratings affect a firm's cost of capital? The Review of Financial Studies, 23, 4324–4347.

Klein, B., Leffler, K. B. (1981). The role of market forces in assuring contractual performance. The Journal of Political Economy, 89, 615–641.

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

Klusak, P., Alsakka, R., ap Gwilym, O. (2015). The impact of ESMA regulatory identifiers on the quality of ratings. Bangor Business School Working Paper, 1–29.

Klusak, P., Alsakka, R., ap Gwilym, O. (2017). Does the disclosure of unsolicited sovereign rating status affect bank ratings? British Accounting Review, 49(2), 194–210.

Krylova, E. (2016). Determinants of euro-denominated corporate bond spreads. ECB - Working Paper Series.

Kwast, M. L. (1989). The impact of underwriting and dealing on bank returns and risks. Journal of Banking and Finance, 13, 101–125.

Lane, P. R. (2013). The European sovereign debt crisis. The Journal of Economic Perspectives, 26, 49–67.

Leanza, L. (2018). Bail-in vs bail-out: Bank resolution and liability structure. Working paper. University Cattolica del Sacro Cuore, Milan.

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

Low, H., Meghir, C. (2017). The use of structural models in econometrics. Journal of Economic Perspectives, 31(2), 33–58.

Lucarelli, C. (2006). An analysis of the medicare prescription drug benefit. PARC Working Paper Series, WPS 06-08.

Lugo, S., Croce, A., Faff, R. (2015). Herding behavior and rating convergence among credit rating agencies: Evidence from the subprime crisis. Review of Finance, 19(4), 1703–1731.

Mason, J. R., Rosner, J. (2007). Where did the risk go? How misapplied bond ratings cause mortgage backed securities and collateralized debt obligation market disruptions, Working Paper.

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

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. Econometrica, 57(5), 995–1026.

Mellios, C., Paget-Blanc, E. (2006). Which factors determine sovereign credit ratings? The European Journal of Finance, 12, 361–377.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance, 29, 449–470.

Michaelides, A., Milidonis, A., Nishiotis, G. P., Papakyriakou, P. (2015). The adverse effects of systematic leakage ahead of official sovereign debt rating announcements. Journal of Financial Economics, 116, 526–547.

Miles, D., Yang, J., Marcheggiano, G. (2012). Optimal bank capital. Economic Journal, 123, 1–37.

Milidonis, A. (2013). Compensation incentives of credit rating agencies and predictability of changes in bond ratings and financial strength ratings. Journal of Banking and Finance, 37(9), 3716–3732.

Modigliani, F., Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. The American Economic Review, 48, 261–297.

Möllers, T. M. J., Niedorf, C. (2014). Regulation and liability of credit rating agencies – A more efficient European law? European Company and Financial Law Review, 3, 333–363.

Moody’s. (2011). Policy for Withdrawal of Credit Ratings.

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. The American Economic Review, 92(4), 874–888.

Morkoetter, S., Stebler, R., Westerfeld, S. (2017). Competition in the credit rating Industry: Benefits for investors and issuers. Journal of Banking and Finance, 75, 235–257.

Moyen, N. (2004). Investment-cash flow sensitivities: Constrained versus unconstrained firms, Journal of Finance, 59, 2061–2092.

Myerson, R. B. (2014). Rethinking the principles of bank regulation: A review of Admati and Hellwig’s The Bankers’ New Clothes. Journal of Economic Literature, 52, 197–210.

Nozawa, Y. (2017). What drives the cross-section of credit spreads? A variance decomposition approach. Journal of Finance, 72(5), 2045–2072.

OJEU (2012). Supplementing Regulation (EC) No 1060/2009 of the European Parliament and of the Council. Commission Delegated Regulation (EU), No 946/2012

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

Packer, F., Tarashev, N. (2011). Rating methodologies for banks. BIS Quarterly Review June, 39–52.

Pakes, A., Pollard, D. (1989). Simulation and the asymptotics of optimization estimators. Econometrica, 57(5), 1027–1057.

Partnoy, F. (1999). The Siskel and Ebert of financial markets?: Two thumbs down for the credit rating agencies. Washington University Law Quarterly, 77, 619–714.

Partnoy, F. (2006). How and why credit ratings agencies are not like other gatekeepers, University of San Diego Legal Studies Research Paper Series, 59–102.

Payne, J. (2014). The role of gatekeepers. Oxford Legal Studies Research Paper No. 22/2014 Oxford Handbook of Financial Regulation.

Pettit, J., Fitt, C., Orlov, S., Kalsekar, A. (2004). The new world of credit ratings. UBS Investment Bank Research Report.

Peura, S., Keppo, J., Bank, S. (2006). Optimal bank capital with costly recapitalization. The Journal of Business, 79(4), 2163–2201.

Pfleiderer, P. C. (2010). On the relevancy of Modigliani and Miller to banking: A parable and some observations. Unpublished working paper. Stanford University, Stanford, CA.

Poon, W. P. H. (2003). Are unsolicited credit ratings biased downward? Journal of Banking and Finance, 27, 593–614.

Poon, W. P. H., Firth, M. (2005). Are unsolicited credit ratings lower? International evidence from bank ratings. Journal of Business Finance and Accounting, 32, 1741–1771.

Poon, W. P. H., Lee, J., Gup, B. E. (2009). Do solicitations matter in bank credit ratings? Results from a study of 72 countries. Journal of Money, Credit and Banking, 41, 285–314.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. Journal of Financial Intermediation, 13, 156–182.

Repullo, R., Suarez, J. (2013). The procyclical effects of bank capital. Review of Financial Studies, 26, 452–490.

Roengpitya, R., Tarashev, N., Tsatsaronis, K. (2014). Bank business models. BIS Quarterly Review December, 55–65.

S&P (2002). Global cash flow and synthetic CDO criteria: CDOs of structured finance securities.

S&P (2016). Policy: Withdrawals, suspensions, discontinuances, and conversions.

Sangiorgi, F., Spatt, C. S. (2016). Opacity, credit rating shopping and bias. Management Science, 63, 4016–4036.

Santis, R. D. (2014). The euro area sovereign debt crisis: Identifying flight-to-liquidity and the spillover mechanisms. Journal of Empirical Finance, 26, 150-170.

Sauer, R. M. (1998). Job mobility and the market for lawyers. The Journal of Political Economy, 106(1), 147–171.

Sauer, R. M. (2015). Does it pay for women to volunteer? International Economic Review, 56(2), 537–564.

SEC (2003). Report on the role and function of credit rating agencies in the operation of the securities markets.

SEC (2008). Summary Report of issues identified in the commission staff 's examinations of select credit rating agencies.

SEC (2017). Annual report on nationally recognized statistical rating organizations.

Shen, C. H., Huang, Y. L., Hasan, I. (2012). Asymmetric benchmarking in bank credit rating. Journal of International Financial Markets, Institutions and Money, 22(1), 171–193.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. Journal of Banking and Finance, 37, 761–772.

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

Smith, R. C., Walter, I. (2002). Ratings, Rating Agencies and the Global Financial System. Boston: Springer US.

Smith, R., Emshwiller, J. R (2001). Running on empty: Enron faces collapse as credit, stock dive and dynegy bolts. Wall Street Journal.

Strebulaev, I. A., Whited, T. M. (2011). Dynamic models and structural estimation in corporate finance. Foundations and Trends in Finance, 6, 1–163.

Sundararajan, V., Enoch, C., San, J., Hilbers, P., Krueger, R., Moretti, M., Slack, G. (2002). Financial soundness indicators: Analytical aspects and country practices. IMF Occasional Papers.

Sy, A. N. R. (2009). The systemic regulation of credit rating agencies and rated markets. World Economics, 10, 69–108.

Tavakoli, J. M. (2004). Collateralized debt obligations and structured finance: New developments in cash and synthetic securitization. New Jersey: John Wiley and Sons.

The Economist (2007). AAAsking for trouble. The Economist.

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

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

Tversky, A., Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. Cognitive Psychology, 5, 207–232.

Tversky, A., Kahneman, D. (1974). Judgement under uncertainty: heuristics and biases. Science, 185 (4157), 1124-1131.

UCLA: Statistical Consulting Group. (2017). Ordered Logistic Regression. Retrieved May 25, 2017, from https://stats.idre.ucla.edu/stata/output/ordered-logistic-regression/

Valencia, F. (2014a). Banks' precautionary capital and credit crunches. Macroeconomic Dynamics, 18(8), 1726–1750.

Valencia, F. (2014b). Monetary policy, bank leverage, and financial stability. Journal of Economic Dynamics and Control, 47, 20–38.

Van Roy, P. (2013). Is there a difference between solicited and unsolicited bank ratings and, if so, why? Journal of Financial Services Research, 44, 53–86.

Vazquez, F., Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. Journal of Banking and Finance, 61, 1–14.

Vu, H., Alsakka, R., ap Gwilym, O. (2017). What drives differences of opinion in sovereign ratings? The roles of information disclosure and political risk. International Journal of Finance and Economics, 22(3), 216–233.

White, L. J. (2010). The credit rating agencies. Journal of Economic Perspectives, 24, 211–226.

White, R. A., Cole, J. L. (2012). Déjà vu all over again: The causes of U.S. commercial bank failures this time around. Journal of Financial Services Research, 42, 5–29.

Williams, G., Alsakka, R., ap Gwilym, O. (2015). Does sovereign creditworthiness affect bank valuations in emerging markets? Journal of International Financial Markets, Institutions and Money, 36, 113–129.