Credit Rating Risks

Empirical Studies of the Securitization Market

Vivian Marit van Breemen

Credit Rating Risks
Empirical Studies
of the Securitization Market

Vivian M. van Breemen

The academic research studies in this book were performed at Nyenrode Business University. The research has been supported by De Nederlandsche Bank (DNB) and the European Central Bank (ECB).

Design & lay-out: Maaike Disco, proefschriftopmaak.nl
Printed by: Ridderprint.nl
ISBN: 9789089801715

NYENRODE BUSINESS UNIVERSITEIT

Credit Rating Risks
Empirical Studies of the Securitization Market

PHD THESIS

with regard to the doctorate/PhD degree
at Nyenrode Business Universiteit
on authority of the
Rector Magnificus, Prof. dr. Koen Becking
in accordance with the Doctorate Committee.

The public defense takes place on
Friday September 22, 2023
at exactly 4 o'clock

by

Vivian Marit van Breemen

born on May 26, 1993
in Heemskerk
the Netherlands

Examination Committee

Supervisor

Prof dr. Dennis Vink	- Nyenrode Business Universiteit

Other members

Prof dr. Arnoud W.A. Boot	- University of Amsterdam
Prof dr. Jakob de Haan	- Rijksuniversiteit Groningen
Prof dr. Ivo Arnold	- Nyenrode Business Universiteit
Prof dr. Ruud G.A. Vergoossen RA	- Nyenrode Business Universiteit

To my beloved parents – Nico and Marjan van Breemen

Preface

The creation of this dissertation has been an amazing journey. It has allowed me to meet incredibly inspiring people and travel to beautiful places. My first academic paper (Chapter 3) was created in collaboration with Professor Vink and dr. Mike Nawas. The paper also benefitted from feedback of Professor Jakob de Haan and Professor Frank J. Fabozzi. After publishing the paper in De Nederlandsche Bank (DNB) Working Paper Series (WPS), I have presented the paper at several international conferences. For instance, with thanks to Professor Duc Khuong Nguyen, we were invited at the Paris Financial Management Conference in 2019. Shortly after, I was fortunate enough to further take part in many intellectually stimulating discussions on our paper at the American Finance Association (AFA) Conference 2022 in San Diego. Special thanks to Professor John Graham for inviting me over all the way to San Diego. The supervision of Professor Vink and dr. Mike Nawas has greatly helped me to eventually publish the paper in the *Journal of International Financial Markets, Institutions & Money*. Not long after that, my second academic paper (Chapter 2) was published in the *Journal of Financial Services Research*, again with the wonderful guidance of three highly regarded experts in my field; Professor Frank J. Fabozzi, Professor Dennis Vink and dr. Mike Nawas.

I was quite proud when, for my third academic paper (Chapter 4), I was invited by Professor Markus Brunnermeier and Professor Laura Starks to present again at the AFA Conference in 2022. My third paper was published in the European Central Bank (ECB) WPS, for which I would like to thank the Editorial Board of the ECB WPS for their review and invitation to publish in the ECB WPS. With the guidance of Professor Dennis Vink and Professor Frank J. Fabozzi, the paper was published in the Journal *Financial Markets, Institutions & Instruments*.

My fourth academic paper (Chapter 5) is created in collaboration with Professor Dennis Vink, Professor Frank J. Fabozzi and dr. Mike Nawas. The paper benefitted from input of the ECB research seminar participants and was presented at the 2022 Annual Conference of ESCB Research Cluster 3. I would like to thank dr. Diana Bonfirm and dr. Dennis Reinhardt for inviting us to the conference in Lisbon where I was asked to present our findings.

For my fifth and final academic paper (Chapter 6), I am very grateful to be working together with dr. Claudia Schwarz and Professor Dennis Vink. The paper also benefitted from feedback of dr. Klaus Düllmann and the participants of the ECB Research Seminar. I would like to thank Linda Goldberg (Federal Reserve Bank of New York), Patricia Mosser (Columbia SIPA), Loriana Pelizzon (Leibniz Institute for Financial Research SAFE) and Raphael Schoenle (Brandeis University and CEBRA) for their invitation to present our paper during the Central Bank Research Association (CEBRA) Annual Meeting 2023 in New York. I am very excited to have many more fruitful research discussions and to continue working on the paper until its publication.

I will forever be thankful for the great number of professional and personal connections and experiences that this dissertation has provided me.

Table of Contents

Chapter 1

General Introduction

General Introduction

Over the years, regulators, policymakers and supervisors have put significant efforts in trying to improve the functioning of the securitization market. The question remains, however, how effective these efforts (oftentimes in the form of rules and regulations) are and how investors perceive the risks embedded in the market. In an attempt to shed light on this relatively complex landscape, this dissertation aims to provide a better understanding of those risks and the evolution of mitigation attempts by the governing bodies. The goal of this dissertation is then to provide useful new insights for all parties directly or indirectly involved in the securitization market, particularly for regulators, policymakers, supervisors and investors.

This dissertation focuses on answering the following question:

> *To what extent do factors beyond credit ratings affect securities' credit quality, and to what extent do investors rely upon these ratings?*

This introductory chapter explains the key characteristics of the securitization market and covers the main concepts and theories that form the foundation of this dissertation. The different research sub-questions underlying our overall research question are then described, followed by a further outline of the remaining part of this dissertation.

1.1 Securitization design and market overview

Securitization is the process in which various types of loans are bundled together and structured into tradeable securities. These securities can be sold to investors who, in turn, receive the interest and principal payments generated from the underlying pool of loans. The securitization process starts with the originator (i.e., a bank or other financial institution) which removes the loans from its own balance sheet by selling the asset pool to an issuer[1]. The issuer divides the asset pool into what is known as tranches or note classes, that each have a different of risk and return profile. The level of seniority of each tranche defines the allocation of investment returns (i.e., principal and interest payments) and losses. The seniority level is usually divided into junior, mezzanine and senior tranches. The most senior tranches have the lowest risk as they are the first to receive a return of capital and the last to be allocated losses. However, this also comes with the lowest expected return making them low-risk low-reward assets. The most junior tranches carry the highest risk as they are the first to be allocated losses. However, in return they benefit from the highest expected return making them high-risk high-return assets. The rules for the distribution of principal and interest payments and the allocation of losses are referred to as the waterfall payment structure. Each tranche receives a credit rating that corresponds to the risk level of the tranche (e.g., senior tranche being AAA-rated). The credit ratings are provided by commercial credit rating agencies (CRAs), such as Moody's, Standard & Poor's (S&P), and Fitch Investors Service (Fitch). CRAs provide forward-looking perspectives on the credit quality of debt obligations. The credit quality, or simply put, the capability and preparedness of the debtor to complete payments on its debt obligations, is reflected in the credit rating. The introduction of CRAs allowed issuers to reach many investors that would otherwise have perceived these securities as opaque and complex (Daley et al., 2020). The securitization investor typically ranges from banks, insurers and pension funds (usually holding the safest tranches)[2] to hedge funds, open-ended funds, asset managers and other international investors (usually holding the risky tranches). A stylized example of the securitization design is provided in Figure 1.1.

[1] This entity is a bankruptcy remove legal entity known as special purpose vehicle or special purpose entity.
[2] Other market participants are for example legal advisors, auditors, servicers, trustees and liquidity providers.

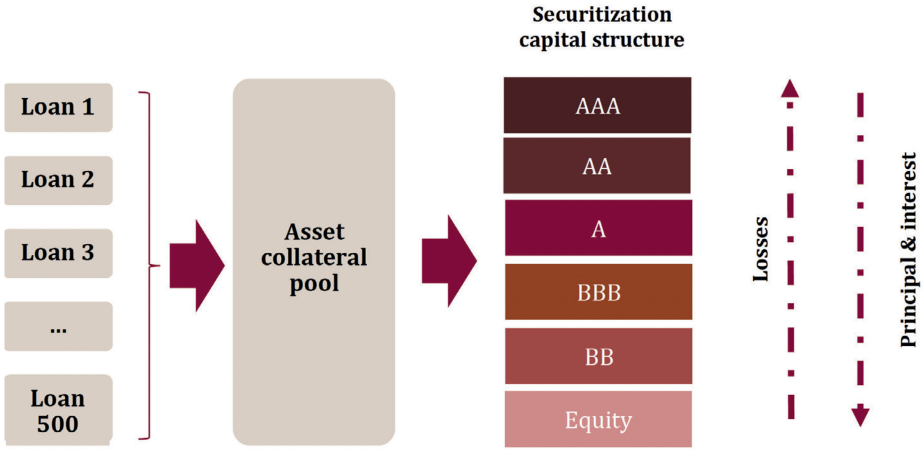


Figure 1.1: Stylized example of securitization design.

The underlying assets of the securitization can be of various types. For example, securitizations backed by a pool of real estate mortgages are called mortgage-backed securities (MBS). Collateralized loan obligations (CLO) are those backed by corporate loans, and asset-backed securities (ABS) are comprised of assets such as student loans, credit card receivables and car loans. Hence, the underlying asset pool in a securitization can vary, but the securitization design remains the same. In this dissertation, I am mainly interested in the issues surrounding the securitization design, rather than solely studying the pool of loans underlying the security. Therefore, I use securitizations with different underlying asset pools interchangeable throughout our study[3]. The added benefit is that it allows us to study a larger and more diversified sample of the securitization market.

Securitization is a financial innovation that was first introduced by US government agencies created by the US Congress in the 1970s to facilitate the development of the residential real estate mortgage market (Jobst, 2008). Only in the late 1990s, European markets followed. The issuance volumes of securitization were

[3] Only in some cases we include specific asset-related variables, such as the average house price for analyses on residential mortgage-backed securities (RMBS).

rapidly increasing in the run up to the 2007-2009 Global Financial Crisis (GFC). Following the GFC, the securitization markets experienced a significant decline in issuance but have since bounced back to unprecedented heights. In terms of size, in 2021, the US market represents roughly 41% and the EU market roughly 7% of the global securitization market (S&P, 2021), with new issue volumes of roughly €233.1 billion and €3.891 billion, respectively, see Figure 1.2.[4]

In this dissertation, I focus on the US and EU securitization markets only. I do so as these market models appear to be quite similar (e.g., compared to those in the Chinese market) and because these markets were hit by the GFC and heavily targeted by regulation thereafter. This creates a unique setting to compare and contrast both markets and investigate the impact of regulation and other market developments before, during and after the crisis.

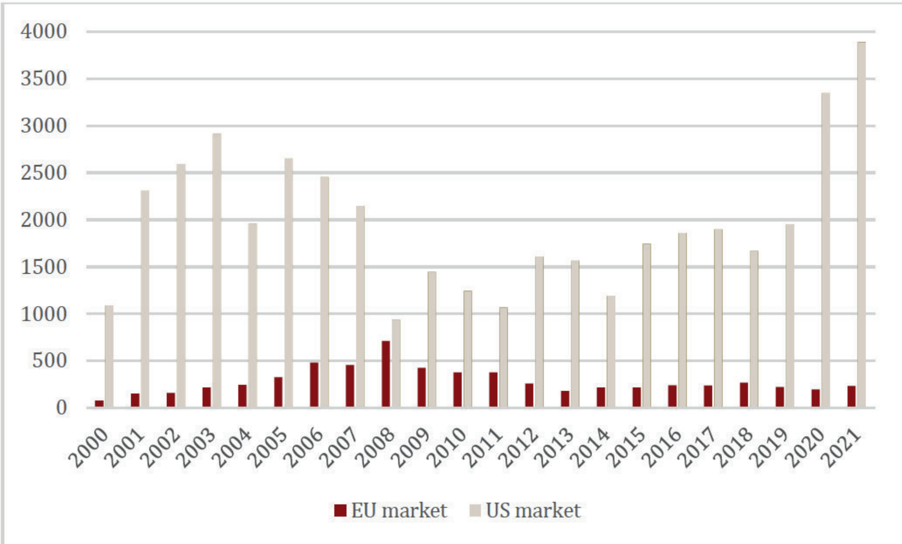


Figure 1.2: Total amount of new issue volumes in the US and EU securitization market (in € billions). Source: Association for Financial Markets in Europe (AFME) and Securities Industry and Financial Markets Association (SIFMA).

[4] The Chinese securitization market rapidly increased in the last decade, representing roughly 40% of the global market in 2021. The remaining markets with a relatively small portion include Japan, Australia, Canada, and Latin America (S&P, 2021).

1.2 Securitizations' rise to fame

Securitization played a key role in the GFC that started in the second or third quarter of 2007. Many market observers argue that the depth and length of the crisis was the result of an overextension of mortgages to weak borrowers (referred to as "subprime borrower") that were securitized and sold to investors. Investors overpriced these securities as the credit ratings attached to the tranches reflected a much more positive outlook than was actually the case. The credit ratings were too optimistic and did not reflect the actual credit risk of a tranche (also known as inflated ratings). When mortgage rates started to rise, debtors, especially homeowners with adjustable-rate mortgages, faced a mortgage payment shock. This resulted in high default rates and consequently high losses for both investors in the senior tranches and junior tranches. Naturally, investors' reliance on credit ratings and their appetite to invest in securitizations were significantly reduced after the crisis[5]. It is alleged that this chain of events was predominantly caused by the CRAs assigning inflated credit ratings as a result of competitive pressures in the rating market and the way in which their business model is structured (see, e.g., De Haan & Amtenbrink, 2011).

1.3 Issuer pays revenue model

The paramount reason why CRAs assign these inflated credit ratings is the way in which revenue is generated by CRAs; the 'issuer pays' revenue model[6]. . In this model, a conflict of interest might arise as the issuer is the key client of the CRA. Issuers are likely to select only the best, most optimistic rating to optimize their profits. Consequently, CRAs might be incentivized to please their clients' (i.e., issuers) wishes by providing more optimistic (inflated)

[5] Ex ante, investors were found to significantly rely on the credit rating in their risk assessment, mainly due to the complex nature of securitization that makes it more difficult for investors to make their own risk assessment (see, e.g., Furfine, 2014).

[6] See, e.g., Flynn & Ghent (2018), Griffin et al. (2013), He et al. (2016) and Zhou et al. (2017).

ratings, rather than those that reflect the securities true credit quality[7].

The conflict of interest between the issuer and CRA is broadly described in literature by two dominant theories: the "rating shopping" and "rating catering" phenomenon. The rating shopping theory states that issuers are able to solicit preliminary credit ratings from numerous CRAs and only select those of their liking. Only the selected CRAs benefit from this process as they receive the full payment of the issuers, while the others receive only a minor fee for breach of contract in return. Following this theory, one might argue that the issuer can put pressure on CRAs to assign ratings that satisfy the wishes of the issuer (i.e., inflated ratings), rather than a rating that solely reflects the underlying credit quality of a security. The rating catering theory builds upon this as CRAs might adjust their credit rating standards based on competitive pressure of their peers. In particular, they might try to match their standards (i.e., by inflating their ratings) to those of their competitors to reduce the chance of rating shopping behavior by issuers.

The unfolding of the global financial crisis has revealed the misfunctioning of the securitization market. The screening capabilities of originators and the rating skills of CRAs have been widely questioned thereafter. Consequently, policymakers and regulators have created more and stricter rules and regulations thereafter. The Dodd-Frank Act[8] was implemented in the US market and, similarly, a variety of regulations have been proposed in the EU[9]. These rules and regulations have, amongst other things, sought to reduce the ability of issuers to shop for ratings. In the US market, this was done by increasing transparency of information in the rating market. In the EU, issuers are now required by regulation to disclose at

[7] The doubts regarding the reliability of credit ratings dates back to before the GFC. For example, in the case of Enron and WoldCom, CRAs were extremely late in adjusting their credit rating when the companies experienced severe difficulties (see e.g., Boot, 2006).

[8] Dodd-Frank Act, 2010, Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Section 941 Subsection 15G.

[9] Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on CRAs.

least two credit ratings of which one should ideally be issued by a small CRA. These and other rules and regulations have also tried to stimulate the entrance of smaller or newer CRAs to reduce the duopoly of Moody's and S&P in the rating market.

1.4 Transformative banking

The process of securitization has transformed the role of banks from an originate-to-hold model to an originate-to-distribute model. Traditionally, banks act as an intermediary between borrowers and depositors, where banks hold and monitor their exposures until maturity. In this originate-to-hold model, risk management is achieved mainly by constructing a well-diversified portfolio. The securitization technique, however, offers banks the opportunity to turn illiquid assets into tradeable liquid securities and remove loans from their balance sheet – a goal sought by banks because of high capital requirements for such loans as explained below. It thereby removes part of the credit exposures from the bank's balance sheet and frees up capital to issue potential new loans. In addition, it provides a mechanism to transfer credit and portfolio risk of banks to capital markets (see, e.g., Aydin & Altunbas, 2016). The securitization process thus intertwines banks with financial markets, creating more risk sharing between them but also make banks vulnerable to volatility in financial markets (e.g., Boot & Marinč, 2010).

However, the originate-to-distribute model also has some serious adverse implications that were revealed during the GFC. Banks tended to reduce their screening and monitoring standards, particularly for those loans that were issued for the sole purpose to securitize. It also enhanced the risk appetite of banks as they knew that the risks will be transferred to third parties anyway. Following these negative implications of the originate-to-distribute model, regulators have introduced the risk retention requirements after the GFC. The risk retention rule requires the originator or sponsor to retain a significant portion (5%) of the securitization on their balance sheet throughout the life of a transaction. The tranche retainer is allowed to choose from different regulatory methods to retain the portion of the securitization. The purpose of this rule is to incentivize banks to make good loans by ensuring that they have some 'skin-in-the-game' (see, e.g., Daley et al., 2019).

1.5 Research sub-questions

To address the overarching research question, '*To what extent do factors beyond credit ratings affect securities credit quality, and to what extent do investors rely upon these ratings?'*, I have established five sub-questions. The first question focuses on the reliance of investors on credit ratings and the factors beyond credit ratings:

1. How do investors rely on credit ratings and other factors beyond credit ratings in determining the funding cost, and how do US and EU market differences impact these relationships?

The second and third sub-questions relate to the implications of the 'issuer pays' business model and competition between CRAs:

2. To what extent is the complexity of a security's design related to rating shopping and rating catering behaviors, and how does the GFC impact these relationships?
3. How does competition between large and small CRAs impact rating quality and rating standards?

The fourth question touches upon the consistency between CRAs in providing their credit ratings:

4. To what extent do CRAs provide consistent and reliable credit ratings given the different levels of creditor protection across US states?

In the fifth and final sub-question, we investigate if differences exist between the various regulatory risk retention methods that are currently in place in the EU market:

5. To what extent do investors and CRAs deviate between the different regulatory risk retention methods in pricing and rating securitization tranches?

The results derived from all the five sub-questions will eventually allow us to answer the overarching research question.

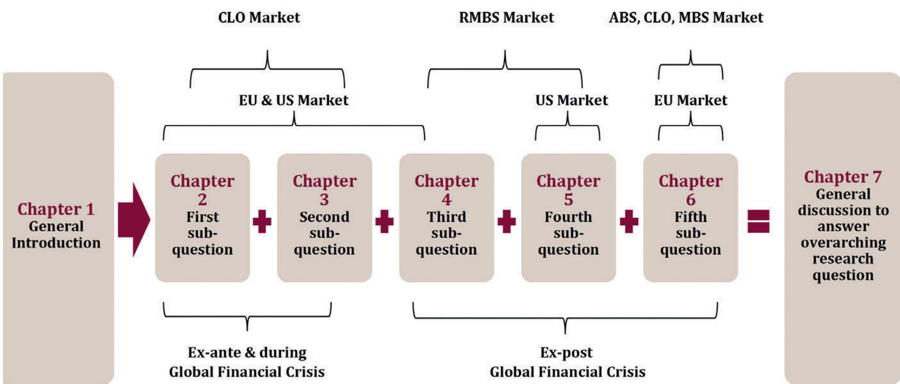


Figure 1.3: Dissertation outline.

1.6 Dissertation outline

Chapters 2 to 6 are based on five stand-alone papers that each answer a separate sub-question. Figure 1.3 visualizes the outlook of this dissertation, including the time period, market and securitization type used in each study.

In **Chapter 2**, we seek to investigate the degree to which investors rely on credit ratings in pricing CLO tranches that were originated and sold between 1997 and

2015 (first sub-question). Furthermore, we compare the behavior of investors in the US and EU primary CLO market. In **Chapter 3,** we study the extent to which the complexity of a security's design is related to credit rating shopping and rating catering behavior in the primary CLO market (second sub-question). We analyze both the US and EU market from 1996 to 2013 and focus specifically on potential differences that might exist ex-ante and ex-post the start of the global financial crisis. In **Chapter 4** we explore our third sub-question by analyzing if, and if so how, competition between small and large CRAs impacts the quality of credit ratings and credit ratings standards. We use primary market data of residential mortgage-backed securities (RMBS) tranches which are originated and sold in the US and EU market between 2017 and 2020. In **Chapter 5**, we restrict our sample to the US only, to investigate the extent to which CRAs provide consistent and reliable credit ratings given the different levels of creditor protection across US states (fourth sub-question). We study RMBS tranches at the time of issuance that were originated and sold between 2017 and 2020. In **Chapter 6**, we focus on the total European securitization market (ABS, CLO, MBS), in the period 2011-2021, to study the impact of the different regulatory risk retention methods on the pricing and rating differences of securitization tranches (fifth sub-question). The quantitative research studies in Chapters 2 to 6 are conducted by applying several ordinary least squares (OLS) and (ordered) logit regression models on pooled cross-sectional data (tranche-level).

Finally, **Chapter 7** discusses the main findings of each chapter and how they, combined, answer the overarching research question. Building upon these results, we specify the contribution and recommendations of our study and conclude by providing limitations of our research and suggested avenues for future research.

References

Association for Financial Markets in Europe (2022, 24 October). AFME securitisation data snapshot: Q3 3033. https://www.afme.eu/Publications/Data-Research/Details/AFME-Securitisation-Data-Snapshot-Q3-2022

Badoer, D. C., Demiroglu, C., & James, C. M. (2019). Ratings quality and borrowing choice. *Journal of Finance, 74*(5), 2619-2665. https://doi.org/10.1111/jofi.12820

Boot, A. W. A. (2006). De toegevoegde waarde van credit ratings. *Maandblad voor Accountancy en Bedrijfseconomie, 80(*3), 108-117.

Boot, A. W. A., & Marinč, M. (2010). Financial innovation: Economic growth versus instability in bank-based versus financial market driven economies. *International Journal of Business and Commerce, 2*(1), 1-32.

Daley, B., Green, B., & Vanasco, V. (2020). Securitization, ratings and credit supply. *Journal of Finance, 75*(2), 1037-1082. https://doi.org/10.1111/jofi.12866

Flynn, S., & Ghent, A. (2018). Competition and credit ratings after the fall. *Management Science, 64*(4), 1477–1973. https://doi.org/10.1287/mnsc.2016.2604

Furfine, C. H. (2014). Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies*, *2*(2), 154–187. https://doi.org/10.1093/rcfs/cft008

Griffin, J. M., Nickerson, J., & Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *Review of Financial Studies*, *26*(9), 2270–2310. https://doi.org/10.1093/rfs/hht036

Haan, J. de, & Amtenbrink, F. (2011). *Credit rating agencies* [Working paper]. DNB Working Paper No. 278. https://doi.org/10.2139/ssrn.1760951

He, J. J., Qian, J. Q. J., & Strahan, P. E. (2016). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067

Jobst, A. (2008, September). *What is securitization?* International Monetary Fund (IMF) Finance & Development. https://www.imf.org/external/pubs/ft/fandd/2008/09/pdf/basics.pdf

Securities Industry and Financial Markets Association. (2008). ESF securitization data report. https://www.sifma.org/wp-content/uploads/2017/05/afme-esf-securitisation-data-report-2008-q4.pdf

S&P Global Ratings. (2021). *Global structured finance 2021 outlook.* https://www.spglobal.com/_assets/documents/ratings/research/100048329.pdf

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: Rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Chapter 2

How much do Investors Rely on Credit Ratings: Empirical Evidence from the US and EU CLO primary market

Journal of Financial Services Research, 2022,
DOI: 10.1007/s10693-021-00372-x

Frank J. Fabozzi
Vivian M. van Breemen
Dennis Vink
Mike Nawas
Austin Gengos

Abstract

We investigate the extent to which investors rely on credit ratings and other factors beyond credit ratings in determining the funding cost for collateralized loan obligations (CLOs) tranches in the period 1997-2015. We find significant differences between the United States (US) and European Union (EU) markets. In the US., we find a much higher and more consistent degree of reliance on credit ratings and other factors in pricing CLOs over time compared to the EU market. Finally, we find that investors in both markets reduce funding costs when rating standards loosened. The regulatory implications are discussed.

Keywords: credit ratings, collateralized loan obligations, regulations, structured finance.

JEL Classifications: G12, G24, G28, G32, L11.

2.1 Introduction

The credit rating industry is dominated by Moody's, Standard & Poor's (S&P), and Fitch. These three credit rating agencies (CRAs) have roughly 91% of the market in Europe and 95% of the market in the US (European Securities and Markets Authorities (ESMA), 2020; Securities and Exchange Commission (SEC), 2020). The market for Collateralized Loan Obligations (CLOs) is a segment of the structured finance securities market[10] and in assigning the credit ratings of CLOs the dominance of only two of CRAs being more pronounced, Moody's and S&P. In the wake of the global financial crisis of 2008, CRAs were accused of assigning biased ratings to structured finance securities such as CLOs (e.g., Griffin et al., 2013) or, more general, to have ascribed ratings that do not appropriately reflect the risks associated with CLOs (see, e.g., Fabozzi & Vink, 2010; Flynn & Ghent; 2018; He et al., 2016; Zhou et al., 2017). Due to the complexity of CLO structures, investors are exposed to the risk that the assigned credit rating does not fully or precisely reflect actual credit risk (Vink et al., 2021).

Concerned that investors may rely too heavily on potentially biased or inflated ratings, attitudes towards the role of CRAs and the dominance of the three largest CRAs in the industry has changed broadly and, in some cases, crystalized at the regulatory level. The Dodd-Frank Act[11] in the United States (US) and regulations[12] in the European Union (EU) have sought to reduce the reliance on credit ratings, especially for structured finance securities. The stated goal is for the market to move away from reliance on credit ratings. The US and EU regulatory responses call for an empirical investigation aimed at better understanding the extent to which investors rely on credit ratings in the CLO market. This improved

[10] In 2018, CLO issuance in the US market amounted to roughly $125 billion (S&P Global, 2018) and at the same time period in the EU market it was approximately €28 billion (Bloomberg, 2019).

[11] Dodd-Frank Act, 2010, Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Section 941 Subsection 15G.

[12] Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on CRAs.

understanding could in turn inform policymakers seeking to improve the effectiveness of legislation.

We investigate the degree to which in the US and EU market investors rely on the credit ratings assigned by CRAs in the pricing the CLO at the time of issuance. Using data of CLO tranches that are originated and sold between 1997 and 2015, we first test the extent to which investors rely on CLO credit ratings by Moody's and/or S&P, as evidenced by the relationship between credit ratings and the quoted margin at issuance. We also examine investor reliance on other factors beyond credit ratings that are specific to the CLO market, which we refer to as "security design" factors. In this way, we gain an understanding as to the degree investors price their investments in CLOs on the basis of credit ratings or on the basis of other factors that influence their investment appetite.

We then consider if such levels of reliance changed over time, through the "steady-boom-bust-recovery" periods observed in the CLO market, and whether there are further differences to be observed in that regard between the US and the EU markets, a consideration prompted by rating models being influenced by the business cycle (Bar-Isaac & Shapiro, 2013; Dilly & Mählmann, 2016). We test whether the patterns observed in the US and the EU differ for large versus small, and frequent versus infrequent issuers in these markets, given suggestions in the literature that investors may vary their reliance on credit ratings, depending on the type of issuer they are dealing with (He et al., 2012). Outside of the field of structured finance ratings, studies have found that CRAs may have varied their rating standards over time (see e.g., Alp, 2013). In the last part of our empirical analysis, we test whether investors take into account changes in rating standards in pricing CLOs in the US and EU markets.

Our results show that in the US market, on average investors rely to a substantially greater extent on credit ratings as they determine the funding cost of CLO tranches than investors do in the EU market. Also, our results show that this greater extent of investor reliance on credit ratings is more consistent over time than in the EU market. Next, we consider if these differences between US and EU investors can be explained by i) business cycles ii) the impact of issuer size or iii) changes in rating standards. We find that they do. First, after the financial crisis, the reliance on credit ratings remained more or less stable in the US but decreased significantly in the EU market. Second, funding cost required by investors in the EU market are different based on issuer size, while investors in the US do not make such differentiation. Third, our results show that investors demand a lower funding cost for CLOs when CRAs loosen their rating standards, more so in the US than in the EU market.

To the best of our knowledge, this paper is the first to compare investors in the US and EU CLO market with respect to the extent to which they rely on credit ratings in pricing CLOs at issue. Our study contributes to a recent body of literature on credit ratings and credit spreads in the structured finance market (see e.g., Marques & Pinto, 2020; Yang et al., 2020), and to the literature on credit rating standards (see e.g. Alp, 2013; Cafarelli, 2020). Our results are relevant to policymakers in the US and EU seeking to improve the effectiveness of their (diverging) legislative frameworks on credit ratings.

The rest of the chapter is organized as follows. Section 2.2 contains a review of the relevant literature related to credit ratings. Section 2.3 describes our CLO tranche data and Section 2.4 presents the results of our empirical tests. Section 2.5 provides a discussion, conclusion and sets out policy implications.

2.2 Literature Review

The academic literature on structured products has benefited greatly from amarked increase both in theoretical and empirical studies of market reliance on credit ratings. In fact, the majority of studies performed on structured products, regardless of the product type, focus somewhat, if not primarily, on the role of the CRAs[13].This is likely due to the widespread belief that CRAs assign favorable ratings, especially to structured finance securities. The issuer-paid business model in place for the entire CRA industry gives CRAs an incentive to cater ratings to issuers' demand (see, e.g., Flynn & Ghent, 2018; Griffin et al., 2013; He et al., 2016; Zhou et al., 2017). CRAs are accused of having contributed to the depth and length of the global financial crisis by assigning favorable ratings to structured finance securities (see, e.g., Flynn & Ghent, 2018; He et al. 2016; Zhou, et al., 2017), either due to poor rating standards in their analysis or because investors relied too heavily on credit ratings in evaluating assets.

In addition, CRAs are found to more likely issue less-accurate ratings during boom periods (see e.g., Bar-Isaac & Shapiro, 2013; Bolton et al., 2012; Dilly and Mählmann, 2016; He et al., 2012). Bar-Isaac and Shapiro (2013), for example, give a number of explanations for this business cycle effect: reputation risk, commercial motives of CRAs to maximize returns and the de-emphasis on credit monitoring by CRAs in periods of low default probability (i.e., in an economic boom).

Another factor that is found to influence rating quality is the size of the issuer. He et al. (2012) examine the role of the CRAs in the rating of private-label residential mortgage-backed securities. They find that larger issuers experience higher funding costs than smaller issuers. Their results are consistent with an earlier study on CRAs and mortgage-backed securities that suggests inaccuracy of ratings related to issuer size (He et al., 2011).

[13] There are studies that focus on other factors besides credit rating that determine the pricing of structured products. For example, Deku et al. (2019), using a sample of 4,201 European originated MBS tranches show that the quality of the trustee has an impact on the pricing of structured finance securities during the most recent global financial crisis.

In the rating of other credit products such as corporate bonds, there is an extensive body of literature on the quality of rating standards (see e.g., Alp, 2013; Becker & Milbourn, 2011; Cafarelli, 2020). Blume et al. (1998) show, using S&P bond ratings, that the number of credit rating downgrades is not caused by a decline in credit quality of corporate debt, but rather by CRAs applying more stringent rating standards in the US market. Agreeing with Blume et al. (1998), Alp (2013) provides more evidence that over the period 1985-2002 credit rating standards varied, with divergent patterns for investment-grade and speculative-grade ratings.

These findings suggest that there are factors outside of the bond structure or collateral itself that affect credit ratings and the pricing of securities, which is consistent with Fabozzi and Vink (2010) and Marques and Pinto (2020) who found that investors look beyond the credit rating in determining the funding cost of structured finance securities. Our assessment of the literature is that rating quality can be impacted by (1) business cycles (see e.g., Bar-Isaac & Shapiro, 2013; Dilly & Mählmann, 2016) (2) issuer size (see e.g., He et al., 2011, 2012), and (3) changes in rating standards (see e.g., Alp, 2013; Cafarelli, 2020). This provides further motivation for our study, in which we seek to examine whether investors take security design factors into account when pricing CLOs at the time of issuance. We build upon these studies and investigate if investors differentiate in the pricing of CLOs between business cycles, issuer size and whether ratings are impacted by changes in rating standards. We differentiate in our analysis between CLOs issued in the US and EU to study differences in the underlying factors which have the greatest impact on the pricing of CLOs and to test the degree to which investors rely on the ratings assigned by CRAs at time of issuance.

2.3 Data and Methods

We begin the process by manually collecting data obtained from *Bloomberg,* which provides a complete universe of 8,324 CLO tranches with a total value of $1.05 trillion, that were issued and sold in the US or EU markets from 1996 up to 2015. For each CLO deal, the dataset provides deal and tranche names, issuer characteristics, price date, the 3-month benchmark/reference interest rate for the floating-rate tranches, credit ratings, balance and primary issuance spread.[14] ches are rated by either Moody's or S&P, or both. There are an insufficient number of CLOs rated by Fitch or other smaller CRAs to enable statistical analyses. Therefore, in our dataset we use only tranches that obtained a rating from Moody's and/or S&P, consistent with the dataset used by Griffin et al. (2013).

We apply several filters to our dataset and remove tranches with incomplete information. Because we are interested in the effect of CLOs deal complexity on the number of credit ratings, we only include in our study CLOs tranches with at least one credit rating disclosed at issue. This reduces our original sample from 8,324 to 7,910. We further discard all tranches with missing transaction or tranche size (14 tranches) and missing information on the funding cost at issue (305 tranches). This filtering resulted in a full sample of 7,591 CLO tranches, of which 5,935 tranches are issued in the US market and 1,656 tranches issued in the EU market. Panels A to D of Table 2.1 reports summary statistics for the US and EU market, respectively.

[14] If fixed-rate tranches were to be included in our study, then it would be necessary to determine the appropriate benchmark yield curve for each tranche in the sample in order to obtain primary issuance spreads that could be consistently compared across the sample. By restricting the tranches in our sample to 3-month floating-rate tranches where the reference rate is the same interest rate benchmark, we avoid this problem. Furthermore, in constructing the final sample, we had to eliminate some tranches due to errant data or metrics that represented vastly atypical observations. For our analysis, we want to have a consistent benchmark for assessing the funding cost.

2.3.1 **Empirical Model**

We investigate the degree to which EU and US market investors rely on the credit ratings assigned by CRAs in the pricing of CLO at the time of issuance. To examine this, we look at the impact of the credit rating of CLOs on the funding cost at issuance in these two markets using ordinary least squares (OLS) regression analysis, which is consistent with He et al. (2016). Based on our literature review in Section 2.2, we also examine investor reliance on other factors beyond credit ratings that are specific to the CLO market (i.e., security design factors). We are primarily interested in the following for each market: (1) the size of the credit rating coefficient controlled for time and issuer fixed effects, (2) the explanatory value of the credit rating coefficient as measured by the adjusted R^2, and (3) the security design factors that investors take into account beyond the credit ratings in determining the price at issue. To achieve this, we perform several regressions that are generally based on the following model:

$$\begin{aligned} Spread_{ijt} = {} & \beta_0 + \beta_1\, Credit\ Rating_{ijt} + \beta_2\, Tranche\ Count_{ijt} + \beta_3\, Capital \\ & Allocation_{ijt} + \beta_4\, Log\ Tranche\ Size_{ijt} + \beta_5\, Log\ Transaction\ Value_{ijt} + \\ & \beta_6\, Rating\ Discrepancy_{ijt} + Issuer\ and\ Market\ Controls_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{2.1}$$

The data vary by year (t), deal (i) and security (j). We control for security-design characteristics, issuer-fixed effects and time-fixed effects. The specification used is an OLS regression with primary issuance spread as the dependent variable, *Credit Rating* as the independent variable and the other variables shown in the model above as control variables. Because the error terms have systematic heterogeneity in our estimation, we use a heteroskedasticity-consistent covariance matrix as suggested by White (1980). Due to the possibility of issuer- and time-fixed effects, which would lead our OLS results to underestimate standard errors of coefficients, we then run the analysis treating each sample as panel data. We achieve this by including the issuance-year effects and we doublecluster for all tranches sold by the same issuer and in the same year in order to build robust standard errors, as recommended by Petersen (2009).

Next, in order to investigate whether changing credit rating standards over time have an impact on the funding costs of a CLO at issuance, we follow Alp (2013) and Liu and Wang (2019) and estimate the following models:

$$R_{it} = \begin{cases} 21 \; if \, Z_{it} \in [\mu_{21}, \infty) \\ 20 \; if \, Z_{it} \in [\mu_{20}, \mu_{21}) \\ \vdots \\ 2 \; if \, Z_{it} \in [\mu_1, \mu_2) \\ 1 \; if \, Z_{it} \in [-\infty, \mu_1) \end{cases} \tag{2.2}$$

$$Z_{it} = \alpha_t + \beta' X_{it} + \epsilon_{it} \tag{2.3}$$

$$E[\epsilon_{it} | X_{it}] = 0, \tag{2.4}$$

Where R_{it} denotes the credit rating of security i in issuance year t. α_t is the intercept for year t, β is the vector of slope coefficients, and Z_{it} is a latent variable that relates to R_{it} in the ranges between different partition points μ_i. R_{it} ranges from 1 to 21 as we have 21 rating categories in our sample. The matrix X_{it} denotes columns with explanatory variables. The variable definitions are given in Section 2.3.2.

In ordered logit models, coefficient values are in units of a latent variable and therefore not economically meaningful, since the year indicator coefficient a_t is not in the same unit as Z_{it}. Therefore, consistent with Alp (2013) and Liu and Wang (2019), we convert a_t into a rating notch, that is the average distance between the partition points. The average rating notch length is calculated as (μ_{20} - μ_1)/19. Dividing the year indicator coefficients, calculated using the ordered logit model defined in Equations (2.2) - (2.4), by the rating notch length, we create an indicator for rating standards. In order to test the impact of rating standards on credit spreads, we use this indicator in model 1, where *Rating Standards* denote the year indicator coefficients divided by the rating notch length in year *t*.

2.3.2 **Variable Construction and Summary Statistics**

2.3.2.1 ***Dependent variable***

The dependent variable of our study is the specific funding cost of CLO tranches. We measure this by the primary issuance spread, simply referred to as spread, which equates to the quoted margin for the tranche (*Spread*). For a given tranche, the funding cost for the issuer is the reference rate plus the quoted margin, where the reference rate represents the portion of the funding cost that is a market-wide benchmark and the quoted margin equates to the portion of the funding cost that is tranche-specific. This latter tranche-specific portion of the funding cost is the additional per annum compensation for the risk faced by investors by purchasing that particular tranche, which means that the quoted margin is, for our purposes, the appropriate measure of the specific funding cost of the CLO tranche. In our study, we use only floating-rate tranches issued at par that were benchmarked off the European interbank offered rate (EURIBOR) for the EU CLO tranches in our study and US dollar London interbank offered rate (USD LIBOR) for the US CLO tranches in our study.[15] For securities issued at par, the *Spread* at issue – the dependent variable in model (1) – equals the quoted margin

[15] EURIBOR reflects the interest rate at which highly credit rated banks can borrow, in euros, from other banks on an unsecured basis. USD LIBOR reflects the interest rate at which highly credit rated banks can borrow, in US dollars, from other banks on an unsecured basis. EURIBOR and USD LIBOR are determined and communicated on a daily basis for a variety of maturities.

between the benchmark rate agreed upon at the date of pricing and the coupon of the initial yield, measured in basis points (bps). Issuance spread is a measure of the risk premium demanded by investors when issued at par. We do not use any tranches issued at a price different from par.

2.3.2.2 ***Independent variables***

The independent variable of the model, *Credit Rating*, is defined as the credit rating of Moody's and/or S&P provided for each tranche at issuance. We measure *Credit Rating* via a numerical scale to convert credit ratings of Moody's (and, in parentheses, S&P) to numerical scores corresponding to the rating notches with respectively 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (AA), 4 for Aa3 (AA–), and so on. Table 2.1 reports summary statistics for the US market (Panels A and C) and EU market (Panels B and D). First, we observe in Panels C and D that with 5,935 tranches our US market dataset has a greater number of data points than our EU market dataset, which counts 1,656 data points. Second, we observe that in the US there are more dual-rated tranches than single-rated tranches, whereas in the EU the opposite is the case. Specifically, in the US market, for 42% (2,508 tranches) of the tranches a single rating was disclosed at issuance and for 58% (3,427 tranches) a dual rating. Slightly more of the single-rated tranches received a rating by S&P (1,492 tranches) than by Moody's (1,016 tranches). In the EU market, 44% (732 tranches) of the tranches were dual-rated and 56% (924 tranches) of the tranches were single-rated, of which we observe a higher number rated by Moody's (647 tranches) than by S&P (277 tranches).

2.3.2.3 ***Control variables***

We report the descriptive statistics and variable distributions in Panels A and B in Table 2.1. We include several control variables to capture security design characteristics of the underlying tranche: the number of tranches the CLO deal of which the tranche is a part; capital allocation of the tranche; tranche value; value of the CLO deal of which the tranche is a part; rating discrepancy, if any, between Moody's and S&P, per tranche; and, finally, the year of issuance of the tranche. Invariably a CLO deal is made up of a number of tranches.

Tranche Count equals the total number of tranches in a corresponding CLO deal. In our total sample, the tranche count[16] per CLO deal ranges from 1 to 23 with a mean of 7.6 for the US market sample and 6.7 for the EU market sample. We construct the *Capital Allocation* measure per tranche as the percent of protection from losses for each tranche in the capital structure. The mean capital allocation in our sample is 23% in the US market and 25% in the EU market. This indicates the percent of cushioning in the capital structure of a CLO deal, against credit losses that a specific tranche could suffer. The cushioning is provided by other tranches in the same CLO deal that are subordinated to the tranche in question. Bloomberg does not readily report values for capital allocation and therefore we had to calculate its value for each tranche manually. This rather laborious calculation was conducted for each tranche on a deal-by-deal basis. *Capital allocation* aligns with credit ratings in those tranches with higher levels of subordinated capital cushioning them against credit losses usually receive a higher credit rating, so even though we label the tranches by credit rating, their credit rating also reflects the subordination structure of cash flows in the entire deal of which the tranche is a part.

We further control for tranche size, measured as the natural logarithm of the face value of a tranche at issuance (*Log Tranche Size*). The mean size of tranches issued in the US market is $98 million. For the EU market, we observe a higher mean tranche size of $250 million. This difference is substantial, and only in part due to there being, as mentioned above, on average more tranches in the US market than in the EU market: deals in the EU were on average 39.2% larger

[16] We excluded one outlier with 29 tranches in one deal.

than in the US market. *Log Transaction Value* equals the natural logarithm of the transaction value (i.e., the face value, at issuance, of the total CLO of which the tranche is a part) measured in million US dollars. The mean *Transaction Value* of the US market sample is $557 million and for the EU market sample $1,140 million. We also control for *Rating Discrepancy,* a dummy variable equal to 1 if at issuance a security rated by Moody's received a different rating from S&P and 0 if not. Finally, we control for time by adding the control variable *Year of Issuance*, which equals the year of tranche issuance and ranges from 1997 to 2015. In our regression, we control for issuer fixed effects (*Issuer Dummy*), an encoded dummy variable for each unique issuer for use as a parameter in our issuer fixed-effects (I.F.E.) regressions.

2.4 Results

In Tables 2.2 to 2.5, we test the degree to which investors rely on the credit rating assigned by CRAs at the time of issuance and identify the security design factors, beyond credit ratings, with a significant impact on the funding cost. In Table 2.2 we report the estimates of the OLS test of Equation (2.1), where we regress the *Spread* at issuance on the *Credit Rating* for the US and EU market for CLO tranches issued from 1997 to 2015. In Tables 2.3 to 2.5 we break down our sample for the EU and US market. The results related to our US market sample are shown in Panels A of Tables 2.3 to 2.5. In Panels B of Tables 2.3 to 2.5 we present our results for the EU market. In Table 2.3, we duplicate the regressions in Table 2.2 but here we split our sample between the EU market and US market. In Table 2.4, we repeat the analysis of Table 2.3, but here we create four-time intervals to test whether credit ratings have a different impact on funding cost for different time periods. In Table 2.5, we break down the sample based on the market share of issuers to test whether credit ratings are priced differently by investors across issuers with varying market shares. In Table 2.6, we estimate the level of rating standard for each year in our sample. Finally, in Table 2.7 we test the impact of rating standards over time on the funding cost at issue.

2.4.1 **Credit rating and the impact on the funding cost for US and EU markets**

We are interested in the size of the credit rating coefficient in Equation (2.1) and the security design factors beyond credit ratings that impact funding cost of CLO tranches. Columns (1) of Table 2.2 and Table 2.3 (Panels A and B) do not include control variables; in the subsequent columns we add control variables related to the structure of the transaction, issuer and time fixed effects.

We first perform our analysis for our full sample (Table 2.2). In column (1) we find a credit rating coefficient of 27.86 (*t-stat*=73.26), statistically significant at the 1% level. This suggests that credit ratings were a significant factor in determining the risk premium. The magnitude and level of significance of the credit rating coefficient remains consistent when we run our model with control variables in columns (2) to (6). In column (6), showing our model with all control variables, we find that the security design factors *Trance Count*, *Capital Allocation*, *Log Tranche Size*, *Log Transaction Value*, and *Rating Discrepancy* are all highly significant in determining the risk premium.

In Table 2.3 we conduct the same analysis as in Table 2.2 but with a split between the US and EU market. We observe striking differences between these two markets. First, we see in the US market a coefficient of 29.98 (*t-stat*=154.3), which is substantially larger than 18.95 (*t-stat*=29.3) for the EU market. So, on average a substantially larger portion of the spread can be attributed to credit ratings in the US market than in the EU market.

Furthermore, for the US market in comparison to the EU market, more of the security design factors are statistically significant. For the US market, investors heavily rely on security design: the coefficients of *Capital Allocation*, *Transaction Value*, and *Tranche Count* are significant at at least a 5% level of significance. Since *Capital Allocation* is already a key input in the CRA models in constructing a credit rating, our findings suggest that investors in the US compared to the

EU market look beyond the credit rating and price additionally for the impact of capital allocation. But they also price additionally for *Transaction Value* and *Tranche Count*, factors which typically are not a key input in CRA models. The findings are robust for controls on CLO vintage, time and issuer fixed effects.

Table 2.1: Summary statistics of CLOs tranches characteristics.

This table reports summary statistics of CLOs issued between 1997 and 2015. 'Spread at issue' is the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Tranche Count' stands for the total number of tranches in the CLO of which the security is a part. 'Capital Allocation' is the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of subordinated tranches and percent of protection from losses in the capital structure. 'Tranche Size' is the face value of the security at issuance in million US dollar, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Transaction Value' is the transaction value measured in million US dollar, 'Log Transaction Value' is the natural logarithm of the transaction value of the security at issuance. 'Rating Discrepancy' that equals 1 if, at issuance, a security had two different credit ratings and 0 if only one rating or no rating differences. Panel A reports summary statistics for the 5,935 US CLO tranches and Panel B for the 1,656 EU CLO tranches.

Panel A: US Market Only

Variable	*Mean*	*Median*	*Std*
Spread at issue	210.8	164	165.6
Credit Rating	5.53	6	4.27
Tranche Count	7.64	7	2.29
Capital Allocation (in %)	0.23	0.19	0.17
Tranche Size	98	30	415
Log Tranche Size	17.2	17.22	1.23
Transaction Value	557	461	613
Log Transaction Value	20.0	19.94	0.49
Rating Discrepancy	0.46	0	0.50

Panel B: EU Market Only

Variable	*Mean*	*Median*	*Std*
Spread at issue	132	70	143.3
Credit Rating	5.82	5	4.98
Tranche Count	6.7	6	3.36
Capital Allocation (in %)	0.25	0.17	0.24
Tranche Size	250	44	662
Log Tranche Size	17.9	17.6	1.66
Transaction Value	1140	521	1560
Log Transaction Value	20.3	20.1	1.0
Rating Discrepancy	0.67	1	0.47

Panel C: Description of Variable Distribution US Market Only

Number of Ratings	Moody’s	S&P
1	1,016	1,492
2	3,427	3,427
Total	4,450	4,926

Number of Ratings both CRA	Freq.	Percent
1	2,508	42.26
2	3,427	57.74
Total	5,935	100.00

Credit rating class	Freq.	Percent
Aaa–Aa3	2,891	48.71
A1–Baa3	2,135	35.97
Non-IG	909	15.32
Total	5,935	100.00

Panel D: Description of Variable Distribution EU Market Only

Number of Ratings	Moody’s	S&P
1	647	277
2	732	732
Total	1,379	1,009

Number of Ratings both CRA	Freq.	Percent
1	924	55.80
2	732	44.20
Total	1,656	100.00

Credit rating class	Freq.	Percent
Aaa–Aa3	799	48.25
A1–Baa3	572	35.54
Non-IG	285	17.21
Total	1,656	100.00

Table 2.2: Regression credit factors on funding cost for CLOs.

This table reports OLS regression of the underlying credit factors on the yield spread (at issuance) of CLOs for the full sample. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1997 and 2015. The dependent variable is the 'Spread at issue', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Tranche Count' stands for the total number of tranches in the CLO of which the security is a part. 'Capital Allocation' is the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of subordinated tranches and percent of protection from losses in the capital structure. 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Log Transaction Value' is the natural logarithm of the transaction value of the security at issuance. 'Rating Discrepancy' that equals 1 if, at issuance, a security had two different credit ratings and 0 if only one rating or no rating differences. 'Years Controls' indicate specifications when year fixed effects were used for years Q1/1997 – Q1/2015. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Rating	27.86***	27.64***	26.87***	27.46***	27.89***	26.30***
	(73.26)	(99.46)	(98.42)	(66.70)	(67.86)	(53.57)
Tranche Count				0.94	-1.40**	2.511***
				(1.53)	(-2.02)	(5.70)
Capital Allocation				30.32***	44.94***	19.25***
				(5.12)	(6.71)	(3.23)
Log Tranche Size				-8.10**	-13.17***	-22.25***
				(-2.09)	(-3.46)	(-9.20)
Log Transaction Value				0.22	4.53***	-3.58***
				(0.25)	(4.50)	(-3.16)
Rating Discrepancy				9.19***	63.47***	-26.31***
				(3.35)	(23.90)	(-10.88)
Year dummy	N	N	Y	Y	N	Y
Issuer dummy	N	Y	Y	N	Y	Y
Observations	7,591	7,591	7,591	7,591	7,591	7,591
Adjusted R-squared	0.567	0.762	0.835	0.836	0.787	0.788

Table 2.3: Regressing credit factors on funding cost for CLOs

This table reports OLS regression of the underlying credit factors on the yield spread (at issuance) of CLOs, comparing the US market with the EU market. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1997 and 2015. The dependent variable is the 'Spread at issue', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. All other variables are defined in Table 2.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for CLOs issued in the US market only; Panel B for CLOs issued in the EU market only.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Rating	31.76***	30.87***	29.98***	31.61***	31.92***	31.86***
	(128.5)	(138.3)	(154.3)	(122.5)	(96.5)	(127.9)
Tranche Count				−2.64***	−2.60***	−1.16**
				(−6.80)	(−3.54)	(−2.13)
Capital Allocation				63.17***	63.12***	50.86***
				(12.28)	(8.44)	(10.04)
Log Tranche Size				2.86***	8.52***	4.08***
				(3.93)	(8.05)	(5.87)
Log Transaction Value				−2.736	−14.7***	−2.39
				(−1.23)	(−3.60)	(−0.65)
Rating Discrepancy				1.63	70.51***	3.04
				(0.69)	(25.3)	(1.28)
Year dummy	N	N	Y	Y	N	Y
Issuer dummy	N	Y	Y	N	Y	Y
Observations	5,935	5,935	5,935	5,935	5,935	5,935
Adjusted R-squared	0.670	0.801	0.898	0.888	0.834	0.900

Panel B: EU Market Only, full sample

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Rating	18.4***	18.75***	18.95***	17.59***	18.79***	19.05***
	(22.94)	(28.74)	(29.30)	(18.97)	(21.78)	(22.1)
Tranche Count				5.62***	1.65	4.37***
				(6.98)	(1.05)	(2.58)
Capital Allocation				2.35	7.59	6.37
				(0.20)	(0.64)	(0.57)
Log Tranche Size				−2.94	−0.47	−0.33
				(−1.46)	(−0.24)	(−0.19)
Log Transaction Value				−16.62***	−15.54***	−10.78*
				(−4.23)	(−2.62)	(−1.84)
Rating Discrepancy				−21.73***	7.42	0.01
				(−3.99)	(1.11)	(0.00)
Year dummy	N	N	Y	Y	N	Y
Issuer dummy	N	Y	Y	N	Y	Y
Observations	1,656	1,656	1,656	1,656	1,656	1,656
Adjusted R-squared	0.410	0.651	0.669	0.590	0.654	0.671

2.4.2 **Time period differences**

In this section we discuss the regression results shown in Table 2.4 for different time periods. We report the results for each of the following four intervals: (1) 1997-2003, (2) 2004-2007, (3) 2008-2011, and (4) 2012-2015 in Table 2.4. We again compare the US (Panel A) with the EU (Panel B) and observe a number of differences across time periods. We have chosen these particular time intervals to reflect the impact of the credit rating on the funding cost under prevailing market circumstances in the global CLO market over time.

The period 1997-2003 can be considered a period of stable growth in CLO issuance, followed in the years 2004-2007 by rapid growth. The years 2008-2011 are the years during which the financial crisis severely disrupted the market, resulting in a dramatic slowdown in new issuance. The final period is one of market recovery, coinciding with the period of key legislation implemented in both the US and EU after the crisis.

Let us examine Table 2.4. We first look at the time period 1997–2003 in columns (1) and (2) of Panel A and B. In column (2) of both panels we find a statistically significant credit rating coefficient of 30.12 (*t-stat*=18.01) in the US market and 29.35 (*t-stat*=14.98) in the EU market. This means that in the time period 1997-2003, in both markets, credit ratings were a significant factor in determining the funding costs. In our model without control variables, we see in column (1) that the R^2 reveals roughly the same explanatory power to credit rating in both markets, with a R^2 of 0.616 for the model of the US market and 0.614 in that for the EU market. Hence, the proportion of variation in funding cost is explained for roughly 61% by the credit rating for both markets in the period 1997 to 2003. In column (2) of Panels A and B we further find that beyond credit rating, *Capital Allocation* and *Tranche Size* were significant factors in determining the funding cost in both markets in that time period. For *Capital Allocation* we find a coefficient of 45.14 (*t-stat*=2.79) in the model for the US market and 50.91 (*t-stat*=2.40) in that for the EU market, and for *Tranche Size* we find a coefficient of 7.28 (*t-stat*=2.45) for the US market, significant at the 5% level, and 8.56 (*t-stat*=3.17) in the EU market but only significant at the 1% level. *Rating Discrepancy* is another significant factor, albeit only in the EU market.

Columns (3) and (4) of Panels A and B show results for the period 2004–2007. We now find a significantly higher credit rating coefficient for the US market than for the EU market, both when looking at credit rating alone in column (3) and for our model containing all control variables in column (4). With credit rating coefficients of 33.63 (*t-stat*=54.24) in the US and 22.93 (*t-stat*=21.85) in the EU market, compared to the preceding period the coefficient in the US increased and in the EU decreased. This means that credit ratings in the US market reported an increase in their impact on the funding cost, whereas in the EU we see the opposite. Furthermore, looking at column (3), the R^2 of 0.766 in the US market in 2004-2007 is significantly higher compared to the R^2 in the previous period, whereas the R^2 in the model for the EU of 0.635 remained similar to the previous period. It therefore appears that in this time period US investors were building up their reliance on credit ratings and, on top of that, the credit rating itself determined a larger portion of the funding cost at issue than in the EU market. If we look at the security design factors, we find similar results for the EU market compared to the time subset 1997–2003. The only difference is that for the US market we find that *Tranche Count* turns significant at the 5% level with a coefficient of –1.7 (*t-stat*=–1.96) in column (4) of Panel A.

We now turn to the period 2008–2011 in columns (5) and (6) of Panels A and B. We find that for the US market the credit rating coefficient with 28.44 (*t-stat*=13.16) in Panel A column (6) decreased slightly compared to the previous periods. However, the decrease in the credit rating coefficient in the EU market was much more drastic, with a coefficient of 8.10 (*t-stat*=5.26) in Panel B column

(6), a drop of about 65% during the collapse of the structured finance markets in the period 2008–2011 compared to the previous period 2004–2007, columns (4) and (6) of Panel B. This suggests that in contrast to the EU, credit ratings in the US market, even during the financial crisis, remained a large and consistent determinant of funding cost.

Looking at credit rating alone in column (5) of Panels A and B, the R^2 reveals a significant higher explanatory power of the credit rating for the US market (R^2 of 0.55) compared to the EU market (R^2 of 0.13). Hence, consistent with the subset 2004–2007, investors in the US market relied to a greater extent on credit ratings alone compared to EU market investors. In fact, the R^2 of 0.13of the model for the EU market is considerably lower than the R^2 in the model for the previous two-year subsets with R^2s of 0.614 in column (1) and 0.635 in column (3).

Next, we study the security design factors and look at some differences between the two markets for the period 2008–2011. We see that the coefficient of *Log Tranche Size* becomes insignificant in the EU while it becomes highly significant with a coefficient of –29.77 (*t-stat*=5.43) in the US market. Thus, for the 2008-2011 period, larger CLO tranches experienced lower funding cost in the US., but we do not observe the same in the EU market. Furthermore, although in the US market we generally see a consistently positive and highly significant coefficient for *Capital Allocation* across time, in the 2008-2011 period it has no significant impact on the funding cost. This is different in the EU market, where we see for the first time a highly significant coefficient for C*apital Allocation* of 64.95 (*t-stat*=3.15) *with a negative sign.* So, in this period, which was characterized by substantial market disruption, our results suggest that in the two markets investors had a different opinion on how capital allocation is to be taken into account in the pricing of CLOs, in addition to how CRAs had already taken it into account in their credit ratings.

Lastly, we move to the period 2012–2015 and find some substantial differences between Panels A and Panel B, columns (7) and (8). First, in line with the previous year subsets 2004–2007 and 2008–2011, we once again find a higher credit rating coefficient in the US market compared to the EU market, with a credit rating coefficient of 30.84 (*t-stat*=143.9) for the US market and 25.12 (*t-stat*=11.74) for the EU market (column (8) of both panels). Having examined all year subsets, we can now see that the size of the credit rating coefficient in the US market is more stable over time than in the EU market. For example, looking at the EU market across time we find credit rating coefficients ranging from 6.76 (*t-stat*=6.18) in column (5) to 29.35 (*t-stat*=14.98) in column (2) of Panel B, while for the US we are looking at a much smaller range from 24.49 (*t-stat*=19.17) in column (1) to 33.63 (*t-stat*=54.24) in column (4).

Second, when looking at credit rating alone in column (7) of Panels A and B, we observe a significantly and dramatically higher R^2 of 0.902 in the model for the US market compared to a R^2 of 0.292 in the model for the EU market. This difference is less pronounced when we turn to our full model in column (8), although the R^2 in the US market remains higher with 0.945 compared to 0.818 in the EU market, in the final period 2012-2015. Hence, our results not only suggest that on average a higher portion of funding cost at issue is determined by the credit ratings in the US market compared to the EU market, but also that in the US market investors increased their reliance on credit ratings in this period, consistent with the previous two time periods 2004–2007 and 2008–2011.

Third, we find security design factors that significantly determine the funding cost at issue in the US market compared to the EU market. In fact, *Tranche Count*, *Capital Allocation*, *Log Transaction Value* and *Rating Discrepancy* all are statistically significant at the 1% level in the US market. For the EU market, beyond credit rating, only *Rating Discrepancy* turns out significant, and only at a 5% significance level in the 2012-2015 period.

To summarize, first, looking at the size of the R^2, investors in the US market compared to the EU tend to rely substantially more on credit ratings in their assessment of the funding cost at issuance. These results are most pronounced in the period leading up to the crisis and in the recovery period after the crisis. Second, our results show a substantially and consistently higher credit rating coefficient for the US compared to the EU market. This means that for the US on average a substantially higher portion of the funding cost is determined by credit ratings. The same applies to the security design factors and their impact on the funding cost. Third, the size of the credit rating coefficient in the US market is more stable over time than in the EU market. In the EU market, investors dramatically reduced the degree to which they relied on credit ratings in pricing CLOs during the aftermath of the structured finance markets collapse in the period 2008-2011. This is far less the case for the US market.

2.4.3 **The impact of issuer size**

In this section, we test whether the credit rating and the other identified factors have different effects on the funding cost depending on the size of the issuer. Our consideration behind this is the notion that investors may price CLOs differently for issuers that are either large and/or tap the market frequently, in line with He et al. (2012) and in line with Cordell et al. (2020), who focus on manager size, which is broadly the same as issuer size in the CLO market where managers typically run their only one CLO issuance program. We examine issuer size in two ways: by market share value and by frequency of issuance.

In columns (1) to (4) of Table 2.5, we split our sample into *Large* and *Small*. Tranches fit into "*Large*" if they are issued and sold by an issuer who is among the top 10% of issuers based on global CLO market share by issuance amount for the period of 1997-2015 in columns (1) and (2), and *Small* refers to all others in columns (3) and (4). In columns (5) to (8), we show regression results based on the number of tranches issued by the issuer. For these simple comparisons, "*Frequent*" issuers refer to those tranches of an issuer that is among the top 10% measured by number of tranches contributed to the total number of CLO tranches issued globally (1997-2015) in columns (5) and (6), and "*Infrequent*" refers to all other CLOs in columns (7) and (8).

We start by comparing the credit rating coefficients for the US with the EU in columns (1) to (8) of Panels A and B. We find roughly similar magnitudes of credit coefficients for the four subsets in the US market. For example, we observe a credit rating coefficient of 32.03 (*t-stat*=83.85) for large issuers in column (2) and a coefficient of 31.72 (=97.91) for small issuers in column (4). When looking at frequent versus infrequent issuers we also find roughly similar coefficients of 31.47 (*t-stat*=90.37) in column (6) and 32.22 (*t-stat*=90.99) in column (8). In the EU market, however, our results suggest that investors *do* differentiate between issuers based on size. For example, we find credit rating coefficients for the large issuers in the EU of 14.54 (*t-stat*=12.40) in column (2) and 25.67 (*t-stat*=26.82) for small issuers in column (4). Comparing frequent with infrequent issuers, in column (6), we observe a substantially lower credit rating coefficient of 16.54 (*t-stat*=14.47) for frequent issuers, compared to 22.91 (*t-stat*=19.24) in column (8) for infrequent issuers. These findings suggest that on average investors in the US market do not differentiate the funding cost based on both of our measures of issuer size, but investors in the EU do, also based on both of our measures of issuer size. In the EU, investors allocate on average a lower funding cost on the basis of credit ratings for tranches that are issued by larger and more frequent issuers compared to those issued by small and infrequent issuers.

Next, turning to the explanatory values in Table 2.6, we find results consistent with Tables 2.3 to 2.5, that is, the R^2 is on average higher and more consistent over different subsamples in the US market compared to the EU market. For the model for the US market, we observe R^2s ranging from 0.65 to 0.69 in Panel A, whereas for the model for the EU market, in Panel B, we find a higher variation, but at a lower level with R^2s ranging from 0.33 to 0.53. This indicates that in the US market, regardless of our measurements for issuer size, investors again tend to rely more, and more consistently, on credit ratings in determining the funding cost at issuance for CLOs, than in the EU market where we see a less consistent and smaller reliance on credit ratings in pricing CLOs.

When we compare the number of significant factors beyond the credit rating coefficient in both markets in Panels A and B, we see a similar pattern: in the EU market credit ratings have a higher impact on funding cost for smaller and infrequent issuers, and a lower impact for larger and frequent issuers, whereas in the US market we do not see a substantial difference in impact on the magnitude of the coefficients on the basis of issuers being large or frequent.

Table 2.4: Regressing credit factors on funding cost for CLOs in different time periods.

This table reports OLS regression of the underlying credit factors on the yield spread (at issuance) of CLOs, comparing the US market with the EU market. The sample is separated by year of issuance, columns (1) – (2) reports subsamples issued between 1997-2003, columns (3) – (4) between 2004-2007, columns (5) – (6) between 2008-2011, and columns (7) – (8) between 2012-2015. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1997 and 2015. The dependent variable is the 'Spread at issue', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. All other variables are defined in Table 2.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for CLOs issued in the US market only; Panel B for CLOs issued in the EU market only.

Panel A: US Market Only

	1997 – 2003		*2004 – 2007*		*2008 – 2011*		*2012 – 2015*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Rating	24.49***	30.12***	29.40***	33.63***	29.34***	28.44***	29.85***	30.84***
	(19.17)	(18.01)	(67.30)	(54.24)	(20.46)	(13.16)	(174.3)	(143.9)
Tranche Count		0.58		−1.7**		13.22*		−2.16***
		(0.16)		(−1.96)		(1.84)		(−3.4)
Capital Allocation		45.14***		73.19***		12.57		42.44***
		(2.79)		(11.35)		(0.20)		(4.04)
Log Tranche Size		7.28**		11.14***		−29.77***		−0.40
		(2.45)		(9.02)		(−5.43)		(−0.35)
Log Transaction Value		−17.75		−9.733		12.85		−19.67***
		(−1.4)		(−1.51)		(0.45)		(−4.86)
Rating Discrepancy		−29.27***		−5.26		−42.81***		17.88***
		(−2.62)		(−1.03)		(−3.13)		(8.412)
Year dummy	N	Y	N	Y	N	Y	N	Y
Issuer dummy	N	Y	N	Y	N	Y	N	Y
Observations	529	529	2,487	2,487	277	277	2,642	2,642
Adjusted R-squared	0.616	0.698	0.766	0.791	0.555	0.842	0.902	0.945

Panel B: EU Market Only

	1997 – 2003		2004 – 2007		2008 – 2011		2012 – 2015	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Rating	26.32***	29.35***	20.73***	22.93***	6.76***	8.10***	18.01***	25.12***
	(15.85)	(14.98)	(24.34)	(21.85)	(6.18)	(5.26)	(6.05)	(11.74)
º		5.75		0.61		12.86**		−0.46
		(1.09)		(0.23)		(1.99)		(−0.09)
Capital Allocation		50.91**		36.65***		−64.95***		−12.16
		(2.40)		(2.69)		(−3.15)		(−0.22)
Log Tranche Size		8.56***		8.42***		−2.16		−3.67
		(3.17)		(3.86)		(−0.36)		(−0.48)
Log Transaction Value		−2.30		−7.81		0.514		−10.13
		(−0.21)		(−0.96)		(0.05)		(−0.33)
Rating Discrepancy		−9.38		5.02		−12.97		30.29**
		(−0.68)		(0.58)		(−0.51)		(2.33)
Year dummy	N	Y	N	Y	N	Y	N	Y
Issuer dummy	N	Y	N	Y	N	Y	N	Y
Observations	297	297	761	761	358	358	240	240
Adjusted R-squared	0.614	0.727	0.635	0.685	0.128	0.547	0.292	0.818

Table 2.5: Regressing credit factors on funding cost for CLOs, seperated by relative size of issuers.

This table reports OLS regression of the underlying credit factors on the yield spread (at issuance) of CLOs, comparing the US market with the EU market. The sample is separated by relative size of issuers, columns (1) to (4) reports subsamples determining issuers size measured by balance contribution and columns (5) to (6) by tranche number. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1997 and 2015. The dependent variable is the 'Spread at issue', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. All other variables are defined in Table 2.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for CLOs issued in the US market only; Panel B for CLOs issued in the EU market only.

Panel A: US Market Only

	Large, Top 10%		*Small, Non-Top 10%*		*Frequent, Top 10%*		*Infrequent, Non-Top 10%*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Rating	32.29***	32.03***	31.44***	31.72***	32.12***	31.47***	31.37***	32.22***
	(78.95)	(83.85)	(101.5)	(97.91)	(92.33)	(90.37)	(89.36)	(90.99)
Tranche Count		−1.84**		−0.19		−1.35**		−0.31
		(−2.39)		(−0.25)		(−2.04)		(−0.33)
Capital Allocation		55.13***		47.3***		57.27***		46.67***
		(7.09)		(6.99)		(8.53)		(6.2)
Log Tranche Size		4.04***		4.17***		2.27**		5.5***
		(3.25)		(5.01)		(2.13)		(5.77)
Log Transaction Value		−6.64		−4.30		−11.32***		1.73
		(−1.36)		(−0.78)		(−2.68)		(0.26)
Rating Discrepancy		5.81*		1.75		8.59***		−2.70
		(1.66)		(0.56)		(2.82)		(−0.73)
Year dummy	N	Y	N	Y	N	Y	N	Y
Issuer dummy	N	Y	N	Y	N	Y	N	Y
Observations	1,927	1,927	4,008	4,008	2,693	2,693	3,242	3,242
Adjusted R-squared	0.690	0.914	0.663	0.893	0.698	0.910	0.650	0.892

Panel B: EU Market Only

	Large, Top 10%		*Small, Non-Top 10%*		*Frequent, Top 10%*		*Infrequent, Non-Top 10%*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Rating	14.33***	14.54***	24.00***	25.67***	17.09***	16.54***	20.34***	22.91***
	(13.51)	(12.40)	(25.13)	(26.82)	(15.32)	(14.47)	(19.47)	(19.24)
Tranche Count		1.74		6.41**		2.55		0.152
		(0.81)		(2.31)		(1.268)		(0.036)
Capital Allocation		25.79*		24.48		−2.59		15.86
		(1.80)		(1.57)		(−0.19)		(0.86)
Log Tranche Size		−7.76**		4.44**		−3.79		4.58*
		(−2.46)		(2.31)		(−1.6)		(1.83)
Log Transaction Value		−7.22		−8.95		−1.43		−14.41
		(−0.96)		(−1.07)		(−0.23)		(−1.48)
Rating Discrepancy		−13.59		11.46		5.65		−10.31
		(−1.49)		(1.079)		(0.66)		(−0.89)
Year dummy	N	Y	N	Y	N	Y	N	Y
Issuer dummy	N	Y	N	Y	N	Y	N	Y
Observations	771	771	885	885	811	811	845	845
Adjusted R-squared	0.331	0.642	0.531	0.759	0.405	0.686	0.424	0.680

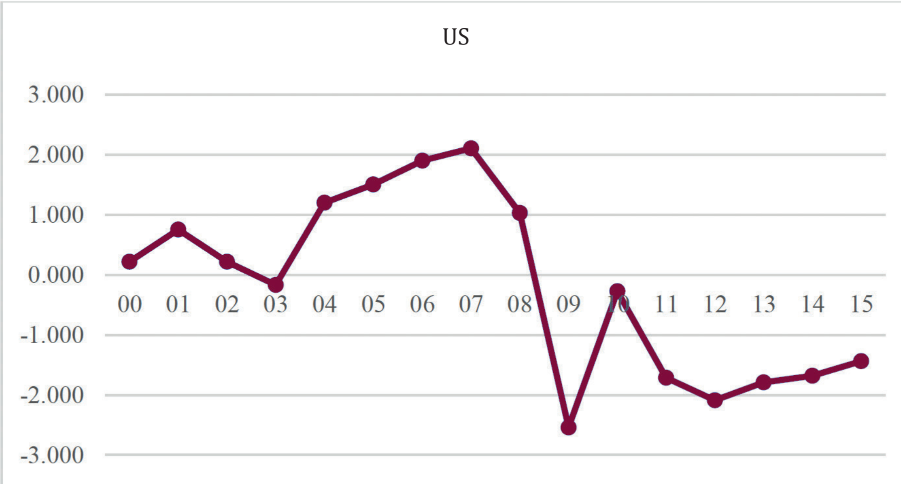


Figure 2.1(a)

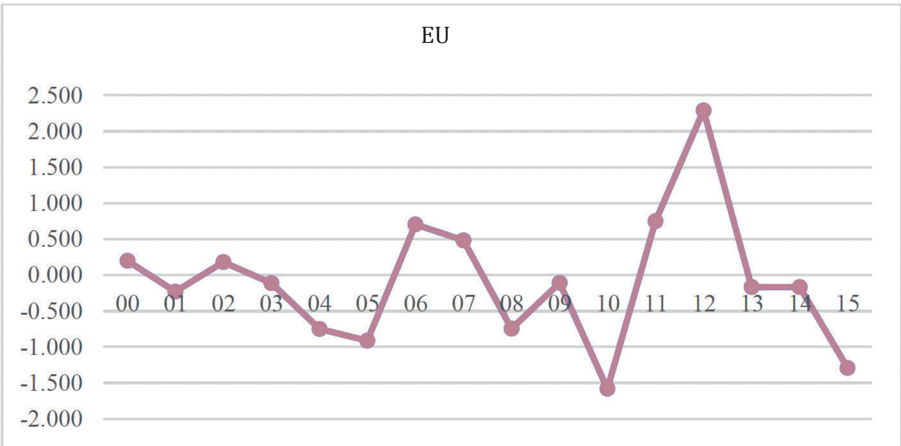


Figure 2.1(b)

Figure 2.1: Plot estimates of the year indicators from the ordered logit model.

Plot estimates of the year indicators from the ordered probit model (Table 2.5), indicating the rating standards. The sample is sorted by year and market of issuance.

Table 2.6. Credit rating standards: Estimation results.

This table reports ordered logit regression of the underlying credit factors on the credit rating, comparing the US market with the EU market. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1999 and 2015. The pattern of year indicator variables is relative to the omitted year, 1999. The dependent variable is the 'Credit Rating' measured as a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. All other variables are defined in Table 2.2. Z-statistics in parentheses and (*), (**), (***) denote significance levels of 10%. 5% and 1%. respectively. Panel A presents results for CLOs issued in the US market only; Panel B for CLOs issued in the EU market only.

Panel A: US market only

	Coefficient	*z-stat*	$\frac{Coefficient * Variable\ Std.Dev}{Rating\ Notch\ Length}$	$\frac{Coefficient}{Rating\ Notch\ Length}$
Tranche Count	0.06***	3.23	0.204	
Capital Allocation	-9.32***	-15.79	-2.515	
Log Tranche Size	0.95***	8.36	0.738	
Log Transaction Value	-1.38***	-18.84	-2.692	
Rating Discrepancy	0.57***	30.69	0.453	
2000	0.14	0.24		0.217
2001	0.47	0.47		0.752
2002	0.14	0.14		0.221
2003	-0.11	-0.23		-0.167
2004	0.76*	1.74		1.203
2005	0.95**	2.24		1.508
2006	1.20***	2.89		1.903
2007	1.33***	3.23		2.108
2008	0.65	1.48		1.032
2009	-1.60	-1.37		-2.540
2010	-0.17	-0.27		-0.270
2011	-1.08**	-2.36		-1.711
2012	-1.32***	-3.00		-2.089
2013	-1.13**	-2.57		-1.789
2014	-1.06**	-2.45		-1.681
2015	-0.91*	-1.92		-1.438
Observations	5.935			
R-squared	0.368			

Panel B: EU market only

	Coefficient	*z-stat*	$\frac{Coefficient * Variable\ Std.Dev}{Rating\ Notch\ Length}$	$\frac{Coefficient}{Rating\ Notch\ Length}$
Tranche Count	0.01	0.61	0.065	
Capital Allocation	-3.15***	-10.51	-1.198	
Log Tranche Size	0.40***	4.60	0.627	
Log Transaction Value	-0.74***	-10.66	0.493	
Rating Discrepancy	0.35***	18.31	0.070	
2000	0.12	0.23		0.197
2001	-0.15	-0.36		-0.232
2002	0.12	0.29		0.183
2003	-0.07**	-1.96		-0.113
2004	-0.47	-1.28		-0.751
2005	-0.58*	1.71		-0.914
2006	0.44	1.32		0.705
2007	0.31	0.89		0.484
2008	-0.47	-1.45		-0.746
2009	-0.07	-0.19		-0.110
2010	-1.00**	-2.57		-1.583
2011	0.47	1.15		0.749
2012	1.44***	3.45		2.292
2013	-0.10	-0.27		-0.165
2014	-0.11	-0.32		-0.168
2015	-0.81**	-2.06		-1.290
Observations	1.656			
R-squared	0.231			

Table 2.7: Credit spreads versus rating standards.

This table reports OLS regression of the rating standards on the yield spread (at issuance) of CLOs, comparing the US market with the EU market. Columns (1) – (2) report the full sample and columns (3) – (4) the AAA sample only. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg between 1999 and 2015. The dependent variable is the 'Spread at issue', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, in basis points. 'Rating Standards' are the coefficient estimates of year indicators for the EU and US market estimated in Table 2.5. All other variables are defined in Table 2.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for CLOs issued in the US market only; Panel B for CLOs issued in the EU market only.

Panel A: US market only

	Full sample		*AAA sample*	
	(1)	(2)	(3)	(4)
Rating Standards	-40.08***	-37.48***	-27.63***	-27.23***
	(-63.96)	(-50.39)	(-57.41)	(-63.01)
Tranche Count		-3.63***		-1.06***
		(-6.58)		(-2.94)
Capital Allocation		34.90***		12.92***
		(6.08)		(4.53)
Log Tranche Size		5.88*		9.13***
		(1.71)		(3.11)
Log Transaction Value		-0.90		3.43***
		(-1.08)		(7.42)
Rating Discrepancy		11.97***		8.56***
		(4.24)		(3.01)
Issuer dummy	Y	Y	Y	Y
Credit rating dummy	Y	Y	N	N
Observations	5,760	5,760	1,720	1,720
Adjusted R-squared	0.907	0.909	0.859	0.873

Panel B: EU market only

	Full sample		*AAA sample*	
	(1)	(2)	(3)	(4)
Rating Standards	-11.65***	-9.58***	-10.06***	-8.65***
	(-3.34)	(-2.71)	(-3.39)	(-2.92)
Tranche Count		-1.56		-3.66***
		(-1.14)		(-4.47)
Capital Allocation		7.81		-1.61
		(0.71)		(-0.28)
Log Tranche Size		-6.04		1.59
		(-1.05)		(0.54)
Log Transaction Value		-3.61*		-1.94
		(-1.77)		(-1.65)
Rating Discrepancy		9.79		3.59
		(1.58)		(0.85)
Issuer dummy	Y	Y	Y	Y
Credit rating dummy	Y	Y	N	N
Observations	1,602	1,602	551	551
Adjusted R-squared	0.735	0.737	0.678	0.695

2.4.4 **Rating Standards**

In this section, we test whether investors identify changes in credit rating standards in the pricing for CLOs issued in the EU and US market in time. First, we present the results of our ordered logit model given in Equations (2.1) to (2.3) that allow us to estimate the level of the credit rating standard for each year in our sample.[17] Second, we examine the impact of rating standards on funding costs for our full sample and triple A sample.[18]

Table 2.6 shows the results of the ordered logit model for the US market in Panel A and for the EU market in Panel B. Column (2) of both Panels show that the tranche-related characteristics are highly significant for both the EU and US market and the signs are consistent between the two markets. For example, in both markets a tranche with a higher capital allocation level will on average have a better rating. The fourth column in Table 2.6, shows what the improvement is in the credit rating measured in the number of notches given a one-standard-deviation increase in capital allocation. For example, a one-standard-deviation increase in capital allocation level on average decreases the credit rating by 2.5 notch in the US market and 1.2 notch in the EU market.[19]

Next, the results in Column (5) allow us to estimate the rating standards over time consistent with Alp (2013). We convert the year indicators to units of rating notches by dividing the year coefficient estimates by the rating notch length. Figure 2.1(a) provides the plot of Panel A column (3) for the US market and Figure 2.1(b) displays the plot for Panel B column (3) the EU market. Interestingly, trends

---

[17] Our sample only includes EU tranches that are issued from 1999 – 2015. To make an accurate comparison on changes in rating standards over time, we exclude all US tranches that are issued before 1999 in this regression.

[18] We use the triple A sample to test if the effects are consistent if we use a fixed rating category, in line with Alp (2013). There are an insufficient number of observations for the other fixed rating categories to enable statistical analyses.

[19] The rating notch length in our sample is (3.75 – (-8.20))/19=0.63. The coefficient of rating discrepancy in Panel A of Table 2.5 is 0.57 with a standard deviation of 0.50 (see Table 2.1, Panel A). Hence, a one-standard-deviation increase in rating discrepancy increases the credit rating by 0.57*0.50/0.63= 0.453 notches.

differ in both markets. Figure 2.1(a) shows that rating standards loosened in the US market until the start of the global financial crisis and became significantly tighter after 2008. In the EU market, rating standards tended to be more stable over time with the exception of 2010, as shown in Figure 2.1(b).

In Table 2.7, we present the regression results of the rating standards and show the impact on the funding cost at issue. If investors perceive the variation in rating standards, then strictly rated CLOs should have lower credit spreads compared to loosely rated CLOs with the same actual rating. We again compare the US market (Panel B) with the EU market (Panel B) and observe fascinating results and differences. In contrast with our expectation, in column 1 of Panels A and B, we find rating standards highly significant with a *negative* sign at the 1% level for both markets. This means that investors demand a lower (higher) funding cost in case the CLO is issued in times of lower (higher) credit rating standards. Looking at the magnitude of the impact in column (1), we see in the US market a coefficient of -40.08 (*t-stat*=-63.96), which is substantially larger than -11.65 (*t-stat*=-3.34) for the EU market. We find similar results for the triple A sample in columns (3) and (4), Table 2.7. This suggests that on average investors in the US and EU market demand lower premiums in situations of loosening credit rating standards, and in the US drastically more so than in the EU market.

2.5 Conclusions and Policy Implications

Investors in the US and in the EU rely considerably on credit ratings in pricing CLOs. However, the divergence between the two markets is striking. First, the reliance is stronger and more consistent over time in the US than in the EU market. Second, investors also take other security design characteristics beyond credit ratings into consideration, such as tranche count and CLO deal size, when determining funding cost for CLO tranches, although more so in the US than in the EU market. Third, our results show that after the global financial crisis the reliance on credit ratings remained more or less stable in the US but dropped markedly in the EU market. So, the level of reliance is much more consistent over time in the US than in the EU market. Fourth, contrary to the findings for the US CLO market, in the EU investors do appear to look to issuer size when they price CLO tranches: they increase their reliance on credit ratings and other factors in the case of smaller or infrequent issuers.

Finally, the impact of tightening and loosening of rating standards on funding costs is negative in both markets, in the US drastically more so than in the EU market, meaning that investors seem to price CLOs tighter when credit standards loosen. The existence of such an inverse relation could point to investors and CRAs at the same time succumbing to market exuberance, thereby exacerbating the business cycle in the CLO market through better (worse) ratings and lower (higher) funding costs. The effectiveness of regulations could therefore be improved if CRAs, financial market associations or market regulators were required to publish relatively frequently (e.g., every 3 to 5 years) how rating standards have tightened or loosened, per segment of the structured finance market, e.g., specifically for CLOs. Currently, this is not the case. Investors could become more aware of these changes, so that they could adapt their risk pricing policies accordingly on a timely basis. Finally, based on our findings, credit departments of investors may hone their investment models to either rely more, or as the case may be, less on credit ratings and other factors beyond credit ratings as they price CLOs.

For further academic research we suggest that for the EU market, in particular, there is a need to improve investor understanding of the pricing dynamics related to CLOs. For the EU CLO market, the models do not explain investor behavior nearly as well as they do for the US market. Given that the Financial Stability Board (2020) predicts that due to changing prudential regulations banks may be set to shift more lending activities from their balance sheet to CLOs, the EU CLO market may well grow even further in magnitude and importance, increasing the importance of better understanding of investor CLO pricing behavior.

References

Alp, A. (2013). Structural shifts in credit rating standards. *The Journal of Finance*, *68*(6), 2435–2470. https://doi.org/10.1111/jofi.12070

Bar-Isaac, H., & Shapiro, J. (2013). Ratings quality over the business cycle. *Journal of Financial Economics*, *108*(1), 62–78. https://doi.org/10.1016/j.jfineco.2012.11.004

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, *101*(3), 493–514. https://doi.org/10.1016/j.jfineco.2011.03.012

Bloomberg. (2019, April 1). *Europe CLOs gear up for the second quarter after beating tough odds.* https://www.bloomberg.com/news/articles/2019-04-01/europe-clos-gear-up-for-second-quarter-after-beating-tough-odds#xj4y7vzkg

Blume, M. E., Lim, F., & Mackinlay, A. C. (1998). The declining credit quality of U.S. Corporate debt: Myth or reality? *The Journal of Finance*, *53*(4), 1389–1413. https://www.jstor.org/stable/117406

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, *67*(1), 85–111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Cafarelli, A. (2020). Creditworthiness risk over years: The evolution of credit rating standards. *Journal of Corporate Accounting & Finance*, *31*(4), 48–59. https://doi.org/10.1002/jcaf.22461

Cordell, L., Roberts, M. R., & Schwert, M. (2020). *CLO performance* [Working paper]. FED Working Paper No. 20-48. https://doi.org/10.21799/frbp.wp.2020.48

Deku, S. Y., Kara, A., & Marques-Ibanez, D. (2019). Trustee reputation in securitization: When does it matter? *Financial Markets, Institutions & Instruments*, *28*(2), 61–84. https://doi.org/10.1111/fmii.12106

Dilly, M., & Mählmann, T. (2016). Is there a "boom bias" in agency ratings? *Review of Finance*, *20*(3), 979–1011. https://doi.org/10.1093/rof/rfv023

Dodd-Frank Wall Street Reform and Consumer Protection Act, Publ. L. No. 111–203, Section 941, Subsection 15G. (2010). https://www.govinfo.gov/link/plaw/111/public/203?link-type=pdf&.pdf

European Securities and Markets Authorities. (2020). *Report on CRA market share calculation*. https://www.esma.europa.eu/press-news/esma-news/esma-reports-annual-market-share-credit-rating-agencies-0

Fabozzi, F. J., & Vink, D. (2010). Looking beyond credit ratings: Factors investors consider in pricing European asset-backed securities. *European Financial Management*, *18*(4), 515–542. https://doi.org/10.1111/j.1468-036X.2010.00577.x

Financial Stability Board. (2020). *Global monitoring report on non-bank financial intermediation 2019*. https://www.fsb.org/wp-content/uploads/P190120.pdf

Flynn, S., & Ghent, A. (2018). Competition and credit ratings after the fall. *Management Science, 64*(4), 1477–1973. https://doi.org/10.1287/mnsc.2016.2604

Griffin, J. M., Nickerson, J., & Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *Review of Financial Studies*, *26*(9), 2270–2310. https://doi.org/10.1093/rfs/hht036

He, J., Qian, J., & Strahan, P. E. (2011). Credit ratings and the evolution of the mortgage-backed securities market. *American Economic Review*, *101*(3), 131–135. https://doi.org/10.1257/aer.101.3.131

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. *The Journal of Finance*, *67*(6), 2097–2137. https://doi.org/10.1111/j.1540-6261.2012.01782.x

He, J. J., Qian, J. Q. J., & Strahan, P. E. (2016). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067

Luo, D., Tang, D. Y., & Wang, S. Q. (2016). *A little knowledge is a dangerous thing: Model specification, data history, and CDO (mis)pricing* [Unpublished manuscript]. School of Finance, Shanghai University of Finance and Economics. https://doi.org/10.2139/ssrn.2730375

Liu, S., & Wang, H. (2019). What affects credit rating informativeness in China? Evidence from updates in the banking sector [Unpublished paper] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3222997

Marques, M. O., & Pinto, J. M. (2020). A comparative analysis of ex ante credit spreads: Structured finance versus straight debt finance. *Journal of Corporate Finance*, *62*, 101580. https://doi.org/10.1016/j.jcorpfin.2020.101580

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053

Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013, amending Regulation (EC) No 1060/2009 on credit rating agencies, Article 8c. (2013). http://data.europa.eu/eli/reg/2013/462/oj

Regulation (EU) No 2017/2402 of the European Parliament and of the Council of 12 December 2017 laying down a general framework for securitisation and creating a specific framework for simple, transparent and standardised securitisation. (2017). http://data.europa.eu/eli/reg/2017/2402/oj

Securities and Exchange Commission. (2020). *Annual report on nationally recognized statistical rating organizations.* https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf

S&P Global. (2018, December 13). *US CLO issuance hits record volume, topping $125B*. https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/leveraged-loan-news/us-clo-issuance-hits-record-volume-topping-125b

Vink, D., Nawas, M., & van Breemen, V. (2021). Security design and credit rating risk in the CLO market. *Journal of International Financial Markets, Institutions and Money*, *72*, 101305. https://doi.org/10.1016/j.intfin.2021.101305

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817. https://doi.org/10.2307/1912934

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: Rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Yang, L., Wang, R., Chen, Z., & Luo, X. (2020). What determines the issue price of lease asset-backed securities in China? *International Review of Financial Analysis*, *72*, 101583. https://doi.org/10.1016/j.irfa.2020.101583

Chapter 3

Security Design and Credit Rating Risk in the CLO market

Journal of International Financial Markets, Institutions & Money, 2021, 72, 101305, DOI:10.1016/j.intfin.2021.101305

Dennis Vink
Mike Nawas
Vivian M. van Breemen

Acknowledgement: *We thank Jakob de Haan (De Nederlandsche Bank) and Frank Fabozzi (EDHEC Business School) for their comments and suggestions on a previous version of the paper. We also thank John Graham (Duke University Fuqua School of Business) for the invitation to participate in the American Finance Association 2020. We also benefited from comments provided by participants of the American Finance Association Conference 2020 and the Paris Financial Management Conference 2019.*

Abstract

In this paper, we empirically explore the effect of the complexity of a security's design on credit rating shopping and rating catering in the collateralized loan obligation (CLO) market in the period before and after the global financial crisis in 2007. We find that complexity of a CLO's design is an important factor in explaining the likelihood that market participants display behaviors consistent with either rating shopping or rating catering. In the period prior to 2007, we observe for more complex CLOs a higher incidence of dual-rated tranches probably reflecting rating catering by credit rating agencies. Conversely, in the period after 2007, for CLOs, it is more likely that issuers shopped for ratings, in particular opting for a single credit rating by Moody's, not by S&P. Furthermore, contrary to what market participants might expect, offering yields at issuance show that investors do not value dual ratings more than single ratings. Looking at the explanatory power of credit ratings for a dual rated CLO, the degree to which investors increase their reliance on credit ratings depends to a large extent on the disclosure of an S&P rating, not Moody's. This suggests that investors recognize credit rating risk by agency in pricing CLOs. In sum, the policy implication is that, to effectively regulate CLOs, the regulatory environment ought to differentiate between complex and non-complex CLOs.

Keywords: collateralized loan obligations, credit ratings, security design complexity, rating shopping, rating catering.

JEL classifications: G14, G24, G28, G32.

3.1 Introduction

The structured finance securities market is frequently named by market observers as an important contributor to the depth and length of the Great Recession that started with the global financial crisis of 2007-2008. The denunciations are typically even stronger when referring to specific segments of the structured finance market, such as collateralized loan obligations (CLOs) or more broadly collateralized debt obligations (CDOs). The credit rating agencies (CRAs) that dominate the market for rating such securities have therefore also been accused of playing a significant part in the crisis, by displaying behaviors that give rise to credit rating risk for investors: the risk that ratings do not fully or accurately reflect the actual credit risk of a security at issuance, by, for example, CRAs assign biased ratings to structured products. Such biased ratings may have caused investors to misprice these securities (see, e.g., He et al., 2012; Kraft, 2015). Despite the widespread criticism of CLOs, as well as of CRAs with respect to CLO ratings, it is generally expected that CLOs will continue to play an important role in the credit markets of the future. This is due to continued use of CLOs as funding vehicles for the shadow banking sector. Consequently, it is important that regulatory requirements regarding the use of credit ratings in the CLO market are improved to mitigate the concerns identified by the financial crisis.

In designing these regulatory requirements, policy-makers so far have not distinguished between more or less complex structured finance securities. Consequently, the de facto view of policy-makers is that all structured finance securities are equally complex. However, during the two decades in the run up to the global financial crisis, financial products such as CLOs became more complex, as the array of transaction features, playing a role in the risk assessment of such products, increased. Furthermore, the security design literature emphasizes that heightened complexity may cause investors to rely more strongly on credit ratings (Arora et al., 2011; Carlin et al., 2013). These observations led us to investigate whether the degree of complexity within the CLO asset class matters for the issuer in deciding to disclose one or two credit ratings at issuance and whether investors value dual ratings over single ratings in pricing complex securities. An empirical investigation of this issue is important because complex products are difficult and time-consuming for investors to evaluate and, as a result, investors in complex products may be tempted to rely on credit ratings and hence be vulnerable to credit rating risk.

In the literature, two dominant theories hypothesize how issuers choose the number of ratings and how CRAs may display market behaviors that give rise to credit rating risk for investors. The first, rating shopping, hypothesizes that CLO issuers solicit ratings from multiple CRAs and only disclose the most favorable ones. According to the rating shopping hypothesis, credit rating risk does not necessarily emanate from CRA behavior but rather from issuers selectively disclosing only the most favorable rating even if CRAs apply best efforts to assess a security's true credit quality. The Dodd-Frank Act in the US, and regulations in the European Union (EU) have sought to reduce the ability of issuers to shop for ratings. In the Dodd-Frank Act, CDO issuers are required to report the results of ratings formally solicited to CRAs. Since 2013, EU regulations require issuers of structured finance securities to disclose at least two ratings.[20]

The second theory is named rating catering and posits that CRAs may succumb to competitive pressures and inflate their credit ratings to gain revenue and market share. According to the rating catering theory, each CRA is seen to stretch its standards to match possible competitors in a 'race to the bottom' where deals receive more favorable ratings as CRAs compete for market share (for CDOs, see Golan et al., 2014). A number of studies that focused on the run-up to the

[20] Regulations in the EU are aimed at promoting a higher level of information disclosure and reducing over-reliance on credit ratings. In 2013, the EU implemented a new regulation that requires at least two credit ratings to be disclosed for newly issued structured products (European Union, 2013).

global financial crisis from 2005 to 2007 showed systematic rating inflation due to a decline in rating standards applied by CRAs to subprime mortgage-backed securities (Ashcraft et al., 2011).

In this chapter, we analyze the complete universe, as reported in *Bloomberg*, of 8,931 CLO tranches originated and sold from November 1996 to May 2013, the month after which the EU regulations regarding dual credit ratings for structured products came into force. We obtain information on the complexity characteristics of the security design of CLOs to examine whether deal complexity matters for the number of ratings disclosed at the moment of issuance. The CLO market is dominated by Moody's and S&P and we note that 62.7% of all CLO tranches with a rating from either Moody's or S&P also received a public rating from the other. Of the dual rated CLOs, 96.3% received equivalent ratings from Moody's and S&P (i.e., 3.7% had split ratings).

Consistent with the rating catering theory, in our first set of tests we find that prior to the Great Recession, CLOs with complexity characteristics were more likely to have dual credit ratings than a single credit rating; hence complex CLO deals are less likely to have been subject to rating shopping. In post-crisis years, however, we do find that complex CLOs were more likely to have one disclosed rating instead of two, a finding that suggests a greater likelihood of rating shopping. In our second set of tests, we examine whether issuers had a particular preference to disclose one CRA over the other when dealing with complexity. We found that for complex CLOs, issuers tended to disclose a Moody's credit rating rather than an S&P rating in the post-crisis period.

While we show in these two sets of tests that complexity mattered in the decision of issuers to report one or two credit ratings on their CLOs, the question remains whether investors were aware of the credit rating risk of rating catering in the case of dual rated tranches and the extent to which they varied their yield requirements to reflect such credit rating risk. The literature emphasizes that, in general, disclosing credit ratings of more than one CRA increases the amount of information available to investors to perform a risk assessment and decreases the required yield at issuance (Bongaerts et al., 2012; Güntay & Hackbarth, 2010; Moreira & Zhao, 2018). Consequently, we ran our third set of tests and found that investors do vary their required yield based on CRA risk assessments, but they clearly differentiate between CRAs. It appears that, for CLO tranches rated by S&P, investors do not significantly rely on the additional information content of a rating by Moody's in their assessment of the required yield. Furthermore, S&P ratings contribute substantially more to the explanatory power of our regressions than Moody's ratings, both before and after the crisis. The latter finding suggests that investors appear to judge that Moody's ratings are catered to match S&P ratings much more so than the other way around. Investors appear to be aware of this and hence price this credit rating risk at issuance.

To the best of our knowledge, this paper is the first to test the relation between the complexity of a CLO design and the number of ratings disclosed. We contribute to a growing body of literature that tries to better understand the complexity of structured finance securities (see e.g., Furfine, 2014; Skreta & Veldkamp, 2009) and rating shopping and catering behaviors (see e.g., Bongaerts et al., 2012; Griffin et al., 2013). Our results are also relevant to policy-makers as it increases the understanding of the extent to which investors rely on credit ratings of S&P and Moody's for complex structured finance securities. This may help policy-makers in the US and Europe in considering the efficacy and efficiency of their diverging regulatory policies on requiring multiple ratings on all structured finance securities, regardless of the complexity of the design characteristics of the securities.

There are six sections that follow. In Section 3.2 we build our hypotheses on the basis of the literature as it relates to credit rating processes for structured finance securities, such as CLO tranches, that have complexity characteristics in their security design. The sample construction and methodology are described in Section 3.3, followed by three sections that describe our empirical results. The empirical findings as to whether complexity of the CLO tranche is related to the number of ratings disclosed at issuance are described in Section 3.4. In order to gain a further understanding of the role of complexity in the number of ratings, in Section 3.5 we report our empirical results as to whether issuers dealing with CRAs in disagreement, i.e., when there is a discrepancy in ratings (in such a circumstance the ratings are often called 'split'), are more likely to disclose both ratings for CLOs that are more complex than for less complex CLOs. While we show that complexity matters in the decision of issuers to report one or two credit ratings on their CLOs, in Section 3.6 we answer the question of whether investors are aware of the credit rating risk caused by rating catering and rating shopping behavior. Finally, in Section 3.7 we conclude.

3.2 Literature on the credit rating process

3.2.1 **Rating Processes**

Globally, Moody's, S&P and Fitch are the three largest CRAs, together representing circa 93% of the market in Europe and 96% of the market in the US (European Securities and Markets Authorities (ESMA), 2018; Securities and Exchange Commission (SEC), 2018). Besides these "Big Three" global agencies, additional smaller CRAs are recognized by regulatory authorities to assess creditworthiness of issues or issuers. The impact of regulation on the quality of information provision on risk assessments of structured products is a current topic of debate (see, e.g., De Haan & Amtenbrink, 2011).

It has been widely argued that the risk assessment processes applied by CRAs played a part in creating the circumstances that led to the global financial crisis and subsequent collapse of the banking system (Bongaerts et al., 2012), as credit ratings were (and remain) widely used in the banking system for determining capital requirements, an important element in prudential supervision (De Haan & Amtenbrink, 2011). The ability of investors and other market participants to rely on CRAs' risk assessments would be diminished if their ratings were to provide inadequate information on the credit quality of securities. Rating failures in the US sub-prime mortgage-backed securities market had systematic consequences, which contributed to the global financial crisis that started in 2007-2008. As a result, since then several regulatory changes have been implemented to improve the accountability and transparency in the rating processes of CRAs (see, e.g., Dimitrov et al., 2015; Kiesel, 2016). These regulations aim to increase the informational content on structured finance securities available to investors and to reduce the potential influence of issuers on rating processes (Bolton et al., 2012). For example, policy-makers in the US introduced via the Dodd-Frank Act the requirement for the SEC to analyze rating processes and to reduce inconsistencies. Regulations in the EU are aimed at promoting a higher level of information disclosure and reducing over-reliance on credit ratings. In 2013, the EU implemented a new regulation[21] that requires at least two credit ratings to be disclosed for newly issued structured products.

The empirical literature on credit rating risk contains numerous studies criticizing the major CRAs for their actions during the buoyant market conditions from 2002 to 2007. Specifically, the literature on the systematic upward bias of asset backed securities and CDOs is substantial. Griffin and Tang (2012) observe frequent upward adjustments to the size of the AAA tranche beyond the output from the rating model. He et al. (2011) find that CRAs granted more generous AAA tranche sizes to issuers that represent a significant source of revenue. Bolton et al. (2012) create a model to explain how CRAs are prone to inflate ratings in cases

[21] Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on CRAs.

where the reputation risk of detection is low. They argue that CDOs are a likely candidate for rating inflation, because such securities have a large proportion of investors that solely rely on CRAs for their credit analysis.

One of the most well-known processes that give rise to credit rating risk is rating shopping: issuers can influence the disclosed credit rating of their securities by only reporting the most optimistic rating after obtaining preliminary ratings from multiple CRAs. Rating shopping is enabled by the 'issuer-paid' business model and the 'winner-takes-most' fee models applied in the rating market. The issuer-paid business model means that the income of CRAs is generated from issuers, notwithstanding that at the same time their task is to objectively rate the securities issued by the same issuers in order for investors to rely on these ratings. Issuers can solicit credit ratings by multiple CRAs and make these public only if they so desire. The CRA, which is selected by the issuer to publicly rate a security, receives a markedly higher upfront fee and also an ongoing payment, while the discarded CRAs only receive a minor contract-breaking fee (see, e.g., Flynn & Ghent, 2018; Griffin et al., 2013; He et al., 2016; Zhou et al., 2017). So, CRAs have an incentive to facilitate favorable ratings (see Flynn & Ghent, 2018; Sangiorgi et al., 2009; Skreta & Veldkamp, 2009). The same result is achieved when issuers engage investment banks to arrange their securities (which includes managing the credit rating process), as they are likely to possess knowledge of the rating algorithms of the CRAs (see, e.g., Griffin et al., 2013). To reduce the rating bias and selective disclosure, Sangiorgi and Spatt (2017) suggest that policy-makers should implement regulatory disclosure requirements aimed at reducing the opacity of correspondence between issuers and CRAs related to the selection process.

Next to the vast body of publications on rating shopping there is another well-established strand in the literature pertaining to credit rating risk, which focuses on the concept of rating catering. Griffin and Tang (2012) find that from 1997 to 2007 model-implied differences in AAA tranche size on average were 10.5%

between S&P and Moody's, even though the two CRAs agreed on the initial AAA tranche size in 96.3% of the cases. The authors suggest that rating catering behavior could explain this high degree of agreement between CRAs, i.e., that the less favorable CRA responded to competitive pressure by assigning AAA capital beyond their rating model to compete with the other agency's more favorable initial rating. Bolton et al. (2012) find that competition amongst CRAs in a duopoly produces less accurate results than having a single, monopoly CRA, regardless of the complexity of rated security. In addition to rating shopping in sub-AAA tranches, He et al. (2016) find rating catering in the AAA tranches. The authors conclude that rating convergence for 97% of dual-rated tranches means that agencies catered to CDO issuers, who would not purchase the ratings unless the CRA(s) assigned a AAA rating to a minimum percentage of the capital structure underlying a CDO. Becker and Milbourn (2011) study the competitive landscape of CRAs and find that the market presence of Fitch correlates with lower quality ratings from S&P and Moody's, suggesting that the duopoly produces suboptimal rating information.

3.2.2 The impact of complexity in structured finance securities on rating processes

Some authors argue that financial institutions may have deliberately introduced complexity into CLO security designs to obscure the troublesome nature of underlying loans (see, e.g., Fahad & Laura, 2017). Of course, the increasing complexity could also have been part of the maturing of the market, but unless investors simultaneously increased their analytical capabilities, they would have had to rely, more and more, on CRAs for analyzing the credit risk of complex products (Arora et al., 2011; Carlin et al., 2013). At the same time, increased complexity also makes it harder for CRAs to assess credit risks. The expected outcome would be an increased likelihood of rating discrepancy, which in turn would stimulate rating shopping; hence, complexity may create opportunities for issuers to adopt rating shopping behavior. In fact, issuers may be tempted to deliberately select complex underlying collateral to generate a broader menu of ratings to shop from (Bakalyar & Galil, 2014; Skreta & Veldkamp, 2009).

The literature emphasizes other causes that could explain rating discrepancy between CRAs. For example, Akins (2018) focuses on the need for higher standards in reporting quality to reduce the chance of rating discrepancy. Morgan (2002) suggests that rating disagreement between Moody's and S&P is higher when there are asset opaqueness problems. Livingston et al. (2007) provide further evidence to support this finding. Iannotta (2006) finds that rating discrepancy between Moody's and S&P is higher for non-banking firms than for banking-firms, while Bowe and Larik (2014) argue that large and profitable companies tend to have a lower likelihood of rating discrepancy. All these studies pertain to the corporate and financial institution bond market where credit ratings are based on the creditworthiness of a (non-financial or financial) corporation, rather than on a pool of assets such as in the structured finance bond market that we are examining. It is important to note that the drivers of credit ratings and therefore split ratings are substantially different for corporate bonds than for structured finance securities. CLOs are by their nature issued exclusively by financial institutions, not by non-financial corporations. The information set out in financial reports pertaining to structured finance securities differs materially from the information provided by corporations. Also, CLOs are multi-sector by design as their credit rating is for an important part derived from the sector diversity in the loans underlying the CLO, whereas the credit risk of bonds issued by corporations can usually be pinpointed to a definable industry sector. Consequently, examining the impact of industry sector or of reporting opaqueness on credit rating discrepancy is not applicable to the structured finance market we are considering, and therefore in Section 3.2.3 we take a look at the way that CLOs are structured and how on that basis CRAs assign credit ratings.

3.2.3 **Measuring complexity in structured finance securities**

Furfine (2014) suggests that complexity in structured finance securities can broadly be defined by the mechanisms of asset pooling, tranching, the deal size and by introducing third-party collaboration. Tranching is a key feature of practically all structured finance securities: it is the layering of the capital structure underlying a CLO transaction in varying tranches of securities, each with a different risk profile. In each CLO, investors in the most senior tranche enjoy the highest percentage of capital underneath them to protect them from losses, whereas investors in the most junior tranches bear the first losses as they have no part of the capital structure subordinated to their tranche. Mezzanine tranches sit in the middle of the capital structure. Typically, issuers seek to tranche the capital structure such that the most senior tranche obtains a AAA rating with the lowest percentage of subordinated capital underneath it as required by the CRA(s), because subordinated capital is expensive for issuers (i.e., investors demand a higher yield for the higher risks of subordinated CLO tranches). Cases where CRAs require a high percentage of capital to be subordinated to the senior tranche in order for such senior tranche to be rated AAA can be deemed to be more complex, i.e., the capital structure is an important indicator of complexity (Fabozzi et al., 2017).

Ghent et al. (2019) analyze the US sub-prime mortgage-backed security market between 2002 and 2007 to test hypotheses linking security design characteristics that indicate deal complexity to the substantial defaults that occurred in that particular segment of the market. They create a deal complexity index based on the number of collateral groups and tranches per deal and prospectus characteristics such as the number of pages dedicated to describing collateral and cash flows. They highlight the potential search costs involved when investors have to analyze securities that have a high degree of complexity as measured by their index. An et al. (2015) measure deal complexity in the commercial mortgage-backed securities segment of the structured finance market, where they use the number of tranches as complexity indicator. He et al. (2016) also use the number of tranches to measure complexity as they analyze mortgage-backed securities. Particular to CLOs, Fahad and Laura (2017) emphasize that deal size and deal structure increase the complexity of CLOs, as larger deals represent more loans, underlying collateral and geographic dispersions and an increase in the number of tranches makes risk and potential return more difficult. Jiang et al. (2018) use the number of tranches and tranche size to measure deal complexity.

3.2.4 **Hypotheses**

Our assessment of the literature on credit rating risk and in particular the potential role of complexity leads us to formulate a number of hypotheses regarding the CLO market. We seek to test these hypotheses. The starting point is the idea that complexity is likely to increase the chance of disagreement among CRAs. If so, CRAs will provide different preliminary opinions to the issuer for the assessment of the same complex product. The disagreement between CRAs might stimulate issuers to display rating shopping behavior and/or may cause CRAs to display rating catering behavior. We follow the methodology initially used by He et al. (2012), and further elaborated in He et al. (2016) and in Jian et al. (2018), where the empirical test for rating shopping is conducted by looking at whether the security is rated by one or by two credit rating agencies, i.e., deals that have one credit rating are more likely to have been shopped compared to deals that have two credit ratings.[22] The direct effect of rating shopping is not visible, as issuers are not obliged to disclose all ratings of preliminary assessments of CRAs (Sangiorgi & Spatt, 2017). We therefore formulate our first hypothesis as follows:

[22] In this framework, He et al. (2016, p.1), for example, argue that "shoppers may censor out pessimistic ratings, thus reducing the number of credit ratings observed empirically, and at the same time reducing the likelihood of observed credit ratings disagreements". It is important to mention that the intention of an issuer to shop for credit ratings or CRA's intention to cater or match the rating, cannot be observed because there is no obligation to report the (preliminary) contacts between CRAs, nor the information of the CRAs on how they looked at or engineered the rating, to match the other rating.

> *H1: Deals that are more complex have a higher likelihood to have been shopped and report only one rating.*

Alternatively, when there is a high degree of agreement among CRAs, rating catering is more likely to have been taken place, as argued by Becker and Milbourn (2011) and Bolton et al. (2012): the less favorable CRA may have responded to competitive pressure by assigning a higher rating beyond their rating model to compete with the other agency's more favorable initial rating. We seek to examine whether complexity in the design of CLOs increases the likelihood of rating catering.

> *H1A: Deals that are more complex have a higher likelihood to have been catered and report two credit ratings that are the same.*

Extending these intuitions, rating shoppers can be hypothesized to select the most favorable rating irrespectively of the CRA that provided the rating. In a duopoly with large market shares by both Moody's and S&P, each CRA is likely to have a strong reputation with investors. Consequently, we expect the issuer to select the most favorable rating irrespective of the specific CRA that assigned the rating.

> *H2: With rating shopping, issuers are indifferent to specific CRAs in their rating selection; they shop only for the most favorable rating.*

If disagreement between two credit ratings does exist and the issuer chooses to disclose both ratings (i.e., the issuer opts to not shop), we expect a larger discrepancy between the credit ratings for more complex deals compared to non-complex CLOs, unless the CRAs succumb to competitive pressures and display rating catering behavior.

> *H3: With no rating catering, complex tranches tend to report a higher degree of rating discrepancy.*

If there is informational value contained in multiple ratings, CLOs with multiple ratings should show a better overall performance compared to single rated CLOs (Griffin et al., 2013). If, however, rating catering is prevalent, dual-rated securities will tend to contain no additional informational content and therefore perform similarly to single rated securities, with rational investors pricing them as such at issuance.[23] Griffin and Tang (2012) conclude that the pre-crisis market for CDOs experienced rating catering because single rated CDOs experienced superior credit performance.

> *H4. With rating catering, dual-rated tranches should have no greater information value in the determination of the required yield than a single rated tranche.*

3.3 Data and Methods

3.3.1 **Data and Filters**

We begin the process of manually collecting data obtained from *Bloomberg,* which provides a complete universe of 10,400 tranches from 1,583 CLO deals with a total value of $1.8 trillion, that were issued and sold in the US or EU markets from November 1996 up to May 2013, when multiple ratings became mandatory in Europe. For each deal, the dataset provides deal and tranche names, issuers characteristics, price date, reference rates, credit ratings, balance and primary issuance spread. All our CLO tranches are rated by either Moody's or S&P, or both.

---

[23] See also Bongaerts et al. (2012) on the effects of credit ratings on credit spreads.

There are an insufficient number of CLOs rated by Fitch, the third of the three globally dominant CRAs, to enable statistical analyses on Fitch ratings. We apply several filters to our dataset and remove tranches with incomplete information. Because we are interested in the effect of CLOs deal complexity on the number of credit ratings, we only include in our study CLOs tranches with at least one credit rating disclosed at issue. This reduces our original sample from 10,400 to 9,112. We further discard all tranches with missing issue data (154 tranches), transaction or tranche size (27 tranches), resulting in a full sample of 8,931 CLO tranches.

3.3.2 **Empirical Model**

We conduct three sets of tests. First, we use a univariate dichotomous (logit) model to study how CLO deal complexity influences the number of credit ratings disclosed at issue. Second, we employ ordered logit regressions to test whether there is a relationship between complexity and the degree of discrepancy of ratings assigned to the same securities by S&P and Moody's. Third, we use ordinary least squares (OLS) tests to investigate the impact of the credit rating on the yield for securities that received one or two credit ratings and the explanatory value as measured by R^2, consistent with He et al. (2016).

Based on our literature review in Section 3.2.3, we identify three key unique explanatory factors of the security design that may determine the CLO's deal complexity: the natural logarithm of the face value of the security at issuance (*Log Tranche Size*), the capital allocation (*Capital Allocation*) measured as the percent of protection from losses in the capital structure, and the total number of tranches in the corresponding CLO of which the security is included (*Tranche Count*).

Our model specifications are as follows:

$$Number\ of\ Ratings_{ijt} = \alpha_0 + \alpha_1 Tranche\ Count_{ijt} + \alpha_2 Tranche\ Size_{ijt} + \alpha_3 Capital\ Allocation_{ijt} + Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt} \tag{3.1}$$

$$Rating\ Discrepancy_{ijt} = \alpha_0 + \alpha_1 Tranche\ Count_{ijt} + \alpha_2 Tranche\ Size_{ijt} + \alpha_3 Capital\ Allocation_{ijt} + Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt} \tag{3.2}$$

$$Spread_{ijt} = \alpha_0 + \alpha_1\ Credit\ Rating_{ijt} + \alpha_2 Tranche\ Count_{ijt} + \alpha_3 Tranche\ Size_{ijt} + \alpha_4 Capital\ Allocation_{ijt} + Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt} \tag{3.3}$$

The data vary by year *(t),* deal *(i)* and security *(j)*. We control for security-specific characteristics, issuer-fixed effects and time-fixed effects. We denote pre- and post- crisis years through the dummy variable *Post*, which we interact with our CLOs deal complexity explanatory variables (*Tranche Count, Log Tranche Size, Capital Allocation*). We do so as credit rating risk is found to be countercyclical: CRAs are more likely to issue less-accurate ratings during boom periods (see e.g., Bar-Isaac & Shapiro, 2013; Bolton et al., 2012; Dilly & Mählmann, 2016; He et al., 2012).

3.3.3 **Variable Construction and Summary Statistics**

3.3.3.1 ***Dependent Variables***

Table 3.1, Panel A reports summary statistics for the total sample. We include tranches with one disclosed rating from either Moody's or S&P, and tranches with ratings from both CRAs. The dependent variable of model (1), *Number of*

Ratings, is defined as the number of credit ratings disclosed for CLOs at issue and is measured using a dummy variable stating whether the CLO had a single or dual rating (i.e., one credit rating by either Moody's or S&P, or a credit rating from both). The sample of 8,931 tranches consists of 3,334 tranches with a single rating disclosed at issue, and 5,597 tranches with a dual rating. Thus, 37.3% of the tranches received a single rating and 62.7% of the traches a dual rating. Panel B of Table 3.1 reports the variable distribution. Slightly more AAA rated tranches are rated by Moody's (2,407 tranches) than by S&P (2,369 tranches), while there are more non-AAA rated tranches by S&P (5,005 tranches) than by Moody's (4,747 tranches). From the investor point of view, the risk of incurring a credit loss is greater for non-AAA than for AAA rated securities, meaning that the importance of obtaining multiple credit ratings may be higher for complex non-AAA rated securities than for complex AAA rated securities.[24] For this reason, we also look at AAA rated securities and non-AAA rated securities separately. We differentiate between pre- and post-crisis years, in order to assess whether the nature of the relationship between complexity and the number of ratings has changed since the crisis.

Next, we analyze rating discrepancy. We consider all tranches rated by Moody's and S&P. In 93.7% of the cases, Moody's and S&P issue the same rating for the CLO. The dependent variable in model (2), *Rating Discrepancy* exists when the tranche is rated unequally by the CRAs. Consistent with Bongaerts et al. (2012), we measure rating discrepancy as the numerical difference in notches that results from subtracting a numerical equivalent of the highest credit rating assigned at issue from the numerical equivalent of the lowest credit rating assigned at issue. This restriction excludes 37.3% of all tranches because they were single rated and 56.3% of all tranches because they received dual, but equal ratings at issue from Moody's and S&P, leaving a sample of 567 CLO (6.4%) tranches with split ratings

---

[24] For example, He et al. (2016) separately test the AAA and sub-AAA tranches of mortgage-backed securities from 2000 to 2006 and find signs of rating shopping in non-AAA rated tranches.

at issue. Looking at Panel C of Table 3.1, the magnitude of rating discrepancy is mostly one notch: of the 567 securities with split ratings, 445 tranches (78%) are rated with one notch difference. Only 72 tranches (13%) are rated with two notches difference and the remaining 50 tranches (9%) are rated with three or more notches difference.

For securities issued at par, the *Spread* at issue – the dependent variable in model (3) – equals the quoted margin between the benchmark rate agreed upon at the date of pricing and the coupon of the initial yield, measured in basis points (bps).[25] Issuance spread is a measure of the risk premium demanded by investors. Unlike the issuance spread, the secondary market spread varies throughout a tranche's life and is affected by factors beyond the credit rating such as the collateral's performance. This is the reason why the issuance spread is used as a measure rather than the secondary spread. The mean issuance spread for the whole sample is 177 bps. In model (3), we split the sample in a dual and single-rated subset.

[25] Almost all CLO tranches are issued at par. Where that was not the case, they were excluded from the sample.

Table 3.1: Summary statistics of CLOs characteristics.

This table reports summary statistics of CLO securities issued in November 1996 up to May 2013. 'Number of Ratings' that equals 1 if, at issuance, a security had two ratings and zero if it had only one rating. 'Rating Discrepancy' stands for the notches difference that results from calculating the numerical difference in credit rating of S&P and Moody's for each security that has two ratings. 'Tranche Count' stands for the total number of tranches in the CLO of which the security is a part of. 'Tranche Size' is the face value of the security at issuance in million US dollar, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Euro Market' is a dummy variable of 1 when the security is issued and sold in the Euro market, and zero if the security is issued and sold in the US market. 'Top Ten Issuer' is a dummy that equals 1 if the issuer is among the top 10% of issuers in the global CLOs market measured by size, and zero otherwise. 'Transaction Value' is the value of the entire deal measured in million US dollars, 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance. 'Year Controls' represent the year of issuance, which equals a dummy of 1 that corresponds to the year the CLO was issued, zero otherwise.

Panel A: Overall Summary Statistics

Variable	N	Mean	Median	Std	P25	P75
Number of Ratings	8,931	0.63	1	0.48	0	1
Rating Discrepancy	8,931	2.60	0	4.19	0	3
Spread at issue	7,706	177	100	184	38	265
Tranche Count	8,931	8.05	7.00	3.44	6.00	10.00
Tranche Size	8,931	114	26	374	14.5	75
Log Tranche Size	8,931	17.35	17.07	1.43	16.49	18.13
Capital Allocation (in %)	8,931	0.22	0.18	0.19	0.09	0.30
Credit Rating	8,931	5.69	6	4.33	1	9
Euro Market	8,931	0.37	0	0.47	0	1
Top Ten Issuer (in %)	8,931	0.33	0	0.47	0	1
Transaction Value	8,931	651	459	857	364	600
Log Transaction Value	8,931	20.00	19.94	0.66	19.71	20.21
Year of Issuance	8,931	2006	2006	3.60	2005	2008

Panel B: Description of Variable Distribution

Number of Tranches in Sample	Credit Rating Agencies	
	Moody's	S&P
AAA	2,407	2,369
Non-AAA	4,747	5,005
Total	7,154	7,374

Number of Ratings	Freq.	Percent
1	3,334	37.33
2	5,597	62.67
Total	8,931	100.00

Top Ten Issuer	Freq.	Percent
0 (lower 90%)	5,993	67.10
1 (top 10%)	2,938	32.90
Total	8,931	100.00

Currency at issuance	Freq.	Percent
Euro Market	3,363	37.66
US Market	5,568	62.34
Total	8,931	100.00

Year of Issuance	Freq.	Percent
Pre-crisis	6,534	73.16
Post-crisis (>2007)	2,397	26.84
Total	8,931	100.00

Panel C: Description of Variable Distribution (continued)

Rating Discrepancy when dual-rated	Full Sample	
	Freq.	Percent
1	445	78.48
2	72	12.70
3	22	3.88
4	10	1.76
5	4	0.71
6	7	1.23
7	4	0.71
8	2	0.35
10	1	0.18
Total	567	100.00

Tranche Count	Full Sample		AAA		Non-AAA	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
1	109	1.22	67	2.51	42	0.67
2	176	1.97	106	3.98	70	1.12
3	232	2.60	98	3.68	134	2.14
4	468	5.24	201	7.55	267	4.26
5	665	7.45	219	8.23	446	7.11
6	1,359	15.22	341	12.81	1,018	16.24
7	1,503	16.83	391	14.69	1,112	17.74
8	1,207	13.51	349	13.12	858	13.68
9	909	10.18	269	10.11	640	10.21
10	601	6.73	175	6.58	426	6.79
11	428	4.79	103	3.87	325	5.18
12	387	4.33	110	4.13	277	4.42
13	204	2.28	57	2.14	147	2.34
14	226	2.53	56	2.10	170	2.71
15	96	1.07	24	0.90	72	1.15
16	130	1.46	38	1.43	92	1.47
17	72	0.81	21	0.79	51	0.81
18	53	0.59	15	0.56	38	0.61
19	31	0.35	9	0.34	22	0.35
20	17	0.19	5	0.19	12	0.19
21	36	0.40	6	0.23	30	0.48
23	22	0.25	1	0.04	21	0.33
Total	8,931	100.00	2,661	100.00	6,270	100.00

Panel D: Distribution by Year of Issuance and Credit Rating

		One Credit Rating		Two Credit Ratings	
		AAA	Non-AAA	AAA	Non-AAA
Tranche Count	N	666	2668	1995	3602
	Mean	6.68	8.09	7.90	8.36
	Median	6.00	7.00	9.00	8.00
	Std	4.20	3.49	3.21	3.30
Tranche Size	N	666	2668	1995	3602
	Mean	388	46.7	256	33.2
	Median	162	20	191	20
	Std	903	151	452	176
Log Tranche Size	N	666	2668	1995	3602
	Mean	18.43	16.82	18.69	16.80
	Median	18.90	16.81	19.07	16.81
	Std	1.93	1.07	1.46	0.82
Capital Allocation	N	666	2668	1995	3602
	Mean	0.30	0.16	0.38	0.17
	Median	0.26	0.14	0.35	0.15
	Std	0.25	0.14	0.22	0.14
Top Ten Issuer	N	666	2668	1995	3602
	Mean	0.41	0.40	0.31	0.27
	Median	0	0	0	0
	Std	0.49	0.49	0.46	0.45
Transaction Size	N	666	2668	1995	3602
	Mean	872	626	650	630
	Median	500	466	459	446
	Std	134	740	811	842
Log Transaction Size	N	666	2668	1995	3602
	Mean	20.10	20.04	20.05	20.00
	Median	20.03	19.96	19.92	19.92
	Std	0.91	0.67	0.61	0.63
Credit Rating	N	666	2668	1995	3602
	Mean	1	8.13	1.04	7.34
	Median	1	9.00	1	6.00
	Std	0	3.77	0.49	3.54
Euro Market	N	666	2668	1995	3602
	Mean	0.68	0.49	0.29	0.33
	Median	1	1	1	1
	Std	0.47	0.50	0.46	0.47
Year of Issuance	N	666	2668	1995	3602
	Mean	2007	2008	2006	2005
	Median	2007	2009	2006	2006
	Std	3.55	4.30	3.16	2.36

3.3.3.2 ***Design Characteristics of CLO Deal Complexity***

We report the descriptive statistics and variable distributions in Panels A to C of Table 3.1. *Log Tranche Size* equals the natural logarithm of the face value of a tranche at issuance. The mean tranche size over the whole sample is US$114 million. *Capital Allocation* is the level of capital allocatio[26] and the mean is about 18% for single rated tranches and about 24% for dual-rated tranches, with the mean over the whole sample being 22%. *Tranche Count* equals the total number of tranches in a corresponding CLO deal. In our total sample, the tranche count[27] per CLO ranges from 1 to 23 with a mean of 8.05. The majority of the securities in our sample has 6 to 9 tranches (56%). We further denote the variable *Post*, a dummy variable set to one if the tranche is issued after the global financial crisis of 2007 (2,397 tranches) and set to zero if the tranche is issued in or before 2007 (6,534 tranches). We are also interested in the effect of the independent variables before and after the global financial crisis, so we introduce interaction variables with the complexity components and *Post*.

3.3.3.3 ***Control Variables***

We include a number of control variables to capture characteristics of the underlying deal, such as transaction value, credit rating, country of issuance, and year of issuance. *Log Transaction Value* equals the natural logarithm of the transaction value (i.e., the face value, at issuance, of the total CLO of which the tranche is a part) measured in million US dollars. The mean *Transaction Value* of the sample is US$651 million. Consistent with Bongearts et al. (2012), we control for credit quality, i.e., *Credit Rating* in our analysis, and use a numerical scale to convert credit ratings of Moody's (and, in parentheses, S&P) to numerical scores

[26] The industry standard formula to measure the level of credit support via capital allocation for a tranche X (equivalent to the level of internal credit enhancement or subordination level) is: 1 – (% of deal of tranche X + % of deal in more senior tranches).

[27]We excluded one outlier with 29 tranches in one deal.

corresponding to the rating notches with respectively 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (AA), 4 for Aa3 (AA-), and so on. As shown in Panel A and C of Table 3.1, the mean credit rating[28] of the whole sample is between A1(A+) and A2 (A), for the single-rated sub-set it is between A2 (A) and A3 (A-) and for the dual-rated sub-set the mean credit rating is A1 (A+), meaning that dual-rated tranches are, on average, higher rated.

We control for the market share of the issuer. We include a dummy variable that equals one if the issuer is among the top 10% of issuers measured using global CLOs market share, and zero if the issuer is among the remaining 90%. Panel B of Table 3.1 shows that 2,938 tranches are issued by top 10% issuers and 5,993 tranches are issued by the remaining 90% issuers. About 33% of the tranches in the sample are issued by top 10% issuers. In model (3), we also control for issuer fixed effects (Petersen, 2009).

We further control for market factors by including *Euro Market,* a dummy variable set to one if the security is issued in the EU market and zero if issued in the US market. In the full sample, 38% of the securities (3,363 tranches) are issued in the EU and 62% in the US (5,568 tranches). Finally, we control for time by adding the control variable *Year of Issuance*, which equals a dummy of one that corresponds to the year of issuance (ranging from 1996 to 2013) and zero otherwise.

3.4 Complexity of a CLO's Design and the Choice for Multiple Ratings

In this section, we examine whether complexity of the security design of the CLO tranches is related to the number of credit ratings disclosed at issue. Complex CLO tranches with one rating are more likely to have been shopped than those

---

[28] Table 3.1 reports the numerical mean credit rating scores corresponding to the rating notches.

with two credit ratings as described in Hypothesis H1. However, as per H1A, with rating catering we expect that for more complex deals, issuers are more likely to disclose two equivalent credit ratings. Moreover, it is expected that for complex deals, Moody's would cater its rating to match S&P (H2) and vice versa. To examine these issues, we look at two different analyses related to the number of credit ratings reported: 1) the likelihood that at issuance a more complex CLO reports two credit ratings that are the same instead of one credit rating, 2) the likelihood that issuers of more complex CLOs disclose two credit ratings that are the same instead of a rating by Moody's exclusively. We repeat the latter for S&P, i.e., the likelihood that issuers of more complex CLOs report two credit ratings instead of a rating by S&P exclusively.

Before performing a formal analysis, we graphically present the median credit rating of CLOs rated by Moody's and S&P, sorted by year of issuance and number of ratings. We identify four groups that a CLO could belong to. The first is "*Both Equal Ratings*" that contain CLOs that have received two ratings that are the same, one by Moody's and S&P. The second is "*Split Ratings*" that contain CLOs with two ratings that are not the same. The last two, "*Moody's Exclusively*" and "*S&P Exclusively*", represent CLOs that received only a credit rating by Moody's, respectively CLOs that only received a credit rating by S&P.

Figure 3.1 illustrates the median credit rating for Both Equal Ratings and Split Ratings, and median credit rating for Moody's Exclusively and S&P Exclusively from 1996 to 2013. We observe a substantial decrease in the median credit rating for dual-rated CLOs after 2008, and a substantial increase in the median rating provided by S&P exclusively compared to Moody's exclusively in the same period. In the period after 2010, CLO tranches that are rated exclusively by S&P clearly and dramatically report lower ratings compared to tranches rated by Moody's exclusively. This may be explained by the substantial reputation loss suffered by S&P during the financial crisis (see, e.g., Baghai & Becker, 2018) and their reaction by tightening standards thereafter, causing S&P since then to provide less favorable ratings than its competitor Moody's.[29] This would also explain the substantially smaller number of dual-rated deals post-crisis that report a lower median credit rating, because we would expect it to be less likely that S&P catered its rating to match that of Moody's. Figure 3.2 confirms the trend that since 2008 a substantial lower number of CLOs are disclosed with split ratings. Before 2008, rating discrepancy was most pronounced between 2004 to 2007.

To control for other possible factors, we move to a multivariate regression framework. For our regression analysis in Equation (3.1), the number of credit ratings is the dependent variable and we segment the sample into two mutually exclusive partitions: *Both Equal Ratings* and *Single Rating*. The presence of deal complexity factors are the primary independent variables and we include *Tranche Count*, *Log Tranche Size* and *Capital Allocation*. Table 3.2 report the estimates of the logit tests of Equation (3.1), where we regress the *Number of Ratings* on CLOs deal complexity factors. We further report specifications for AAA and non-AAA rated tranches. In Table 3.3, we repeat the analysis of Table 3.2, but here we further segment *Single Rating* into two mutually exclusive partitions. The first is *Moody's Exclusively* that represent CLOs that received a credit rating from Moody's but not from S&P. The second is *S&P Exclusively*, that contains only CLOs that were rated by S&P exclusively.

[29] One such reputation loss is caused by the US government suing S&P for mispresenting the credit risk of complex financial products.

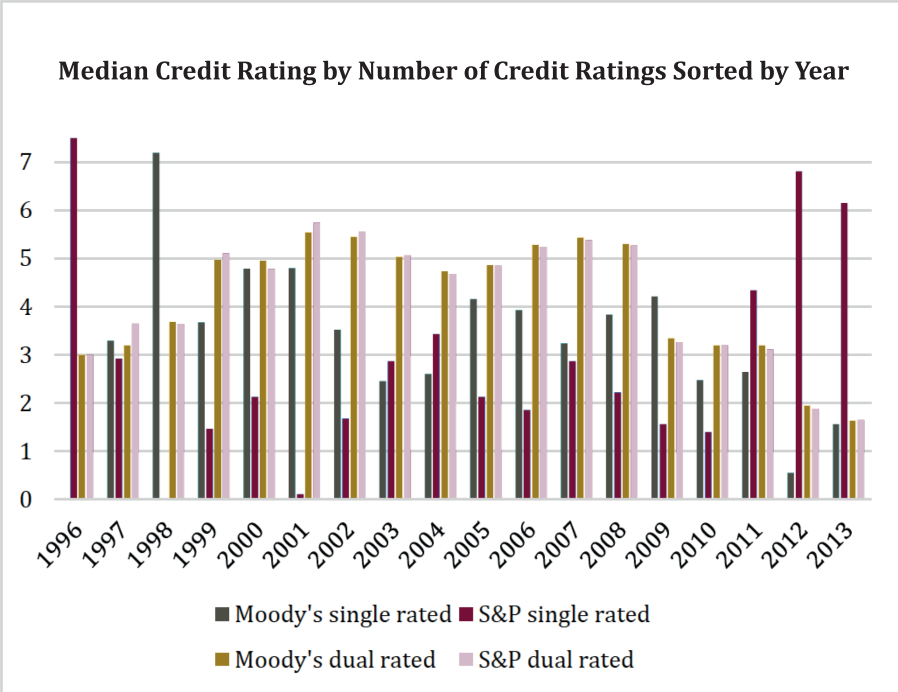


Figure 3.1: Disclosed credit rating at issue of Moody's and S&P sorted by year.
This figure illustrates the median credit rating of Moody's and S&P sorted by issuing year and number of ratings. The sample includes all tranches for which CLOs received either one or two credit ratings from Moody's or S&P disclosed at issuance originated between 1996 and 2013. We convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on.

3.4.1 **Number of ratings disclosed at issuance**

In Table 3.2 we report the results of logit regressions with the number of credit ratings described above as the dependent variables. Panel A of Table 3.2 presents odds ratios of regressions for the full sample. The pseudo R^2 in columns (1) to (8) are around 30%, i.e., our model explains 30% of the variation in the number of credit ratings. In columns (1) to (8), we find consistent, positive and highly significant results for the complexity factors *Tranche Count*, *Log Tranche Size* and *Capital Allocation.*

In column (1) we find that the odds ratio of *Tranche Count* is positive significant (ζ-stat=3.72), indicating that a one standard deviation change in *Tranche Count* increases the odds of experiencing two credit ratings by 4%. We test whether the results in column (1) are sensitive to modifications, by rotationally removing complexity indicators in columns (2) to (4). We observe, overall, that the complexity indicators follow a similar pattern: their coefficients remain positive and significant at a 1% significance level in all cases except for *Tranche Count*, where the coefficients have the correct sign, but are insignificant in columns (3) and (5). The coefficient on *Log Tranche Size* remains significant and stable across all specifications, with odds ratios ranging from 0.24 to 0.35 throughout. The odds ratios of our third complexity factor, *Capital Allocation*, are significantly above two in all specifications. In the first column of Table 3.2 we find that the magnitude of *Capital Allocation's* coefficient increases to an odds ratio of 2.38 (ζ-stat=9.08), indicating that a one standard deviation increase in *Capital Allocation* increases the odds of a dual-rated tranche by 238%. This finding suggests that the security design where a CLO is given a higher capital allocation is associated with a higher likelihood of disclosing two rather than one credit rating at issuance. We also find that, on average, larger issuers are more likely to sell CLO tranches with one credit rating disclosed, when compared to small issuers (odds ratio of -0.26), suggesting that overall issuer size may also play a part in determining the likelihood that issuers engage in rating shopping behavior.

Columns (5) to (8) are constructed to analyze whether there has been a change in the observed pattern since the financial crisis. We look at the complexity characteristics in the period after 2007 using an interaction variable *Post* for each of the complexity factors. Overall, we find the same relationship still holds – the one exception being *Log Tranche Size* in column (6) where we observe a negative significant relationship at the 5% level (ζ-stat=-2.43), what means that on average larger tranches are less likely to disclose two credit ratings in the period after the crisis.

In Panels B and C of Table 3.2, we report results for only AAA and non-AAA tranches, respectively. Looking at the pseudo R^2s of Table 3.2, we can see that it is the highest for non-AAA tranches with 42% (Panel C). The pseudo R^2 is slightly higher for the full sample (Panel A) with 32% than for the AAA tranches sample (Panel B) with roughly 27%. Our observations remain robust with positive and highly significant coefficients for the complexity characteristics with the exception for *Tranche Count*. Interestingly, the coefficient of *Tranche Count* appears to change signs and becomes less significant for the non-AAA sample compared with the AAA sample. Our explanation is that investors in non-AAA compared to AAA CLOs are less concerned about the complex tranche structure because they receive payment only after the AAA has been paid.[30]

Note that we once again observe a post-crisis sign reversal, with this time negative significant odds ratios, at the 1% level for *Log Tranche Size* and *Capital Allocation*. As can be seen in both Panel B and Panel C, *Log Tranche Size* and *Capital Allocation* enter the logistical regression with very strong positive coefficients across all years, but in the post crisis period for these complexity indicators the effect turns from positive into negative. This means that in the period after the crisis, deals with larger tranche sizes and higher capital allocation levels have been more likely to report at issuance only one credit rating than two.

The results in this section indicate that, in the pre-crisis period, for more complex deals issuers tended to disclose, at issuance, two equivalent credit ratings rather than one single credit rating. These findings, both for the larger sample as well as the subsets of AAA and non-AAA CLO tranches, provide empirical evidence that

---

[30] The investors in AAA tranches receive their cash flows with priority, the investors in non-AAA tranches receive their cash flows only after the AAA tranche payment obligations have been fulfilled. That is, in a CLO deal there are always subordinated tranches that support the credit quality of a AAA tranche, and these are the non-AAA rated tranches in the sample. Investors in subordinated tranches of a given deal either have no further subordinated tranches underneath theirs, or to a much lesser extent than the AAA investors that are senior to them in the same deal. Consequently, the investors in non-AAA tranches are less concerned about the number of tranches in a deal than AAA investors.

is contrary to the general idea of rating shopping (H1) but consistent with rating catering (H1A). However, in the period after the crisis, we observe a dramatic change and find evidence that supports rating shopping. In this period, we see that CLO tranches that are larger and those where the AAA rated tranches had higher capital allocation levels are more likely to have a single credit rating rather than dual credit ratings. A possible explanation for these findings is that before the crisis the rating environment for more complex deals made it easier for issuers to put pressure on CRAs to match each other's rating, and that after the crisis, even though issuers still sold complex CLOs, they had fewer opportunities to influence the credit ratings quality because of stricter quality controls within the CRAs themselves, i.e., a reduced likelihood of rating catering.

3.4.2 **Number of ratings disclosed at issuance, variations between Moody's and S&P**

We now shift our attention to each of the CRAs (Moody's and S&P) separately, to assess the extent to which they may have catered their rating to match their competitor for complex CLOs, before and after the crisis. In Panel A of Table 3.3, we take a finer approach in our logit model by including *Moody's Exclusively* and *S&P Exclusively*, as opposed to just *Single Credit Rating*. We first look at the effects of deal complexity on the issuer's preference to disclose two credit ratings at issuance instead of a single credit rating by only Moody's (*Moody's Exclusively*). To do so, in Panel A we exclude all single ratings from S&P (*S&P Exclusively*). In Panel B, we repeat the analysis discussed above, but now we analyze the effect of complexity on tranches that are rated by both agencies compared to tranches that received only a single rating by S&P (i.e., *Moody's Exclusively* are excluded). The model of Panel B explains a substantial higher proportion of variation, denoted by the R^2 (48%), compared to the model in Panel A (24%).

Looking at the results in Panel A, we find highly significant and positive coefficients for all our complexity measures (*Tranche Count*, *Log Tranche Size,* and *Capital Allocation*). This means that when using data across the entire sample time period, issuers of complex CLOs are on average more likely to disclose dual ratings rather than a single Moody's rating. We include the *Post* crisis dummy in columns (5) to (8) and observe similar variations as displayed in Panel A of Table 3.2.

In Table 3.3 Panel B, our results follow the same pattern as in Panel A. We observe substantial differences between Panel A and Panel B when we interact our capital allocation characteristic with *Post*. In Panel B, we find that the relative likelihood of a CLO being rated by both credit rating agencies instead of S&P alone increases with subordination level in the post-crisis period, a result that is significant at the 5% level (ζ-stat=2.44). In Panel A, we find the opposite is the case for Moody's, in that CLOs with higher capital allocation levels are less likely to report two credit ratings but rather a single rating instead (ζ-stat=-3.75). So, our results do not provide evidence that for complex CLOs Moody's and S&P cater their credit ratings to match each other's rating (H2). We see that issuers are more likely to shop for a single credit rating provided by Moody's rather than by S&P especially for CLOs with higher capital allocation levels. This suggests that in the period after the crisis, only Moody's (not S&P) would be prepared to provide the better rating at a higher capital allocation level. It may well be that, consistent with rating shopping, issuers selected only a Moody's rating because Moody's would be the only CRA willing to engineer the deal with higher capital levels to obtain AAA status. In Section 3.5, we further investigate the individual complexity measures through their correlation with the business cycle for split ratings between S&P and Moody's.

3.5 Rating discrepancy between Moody's and S&P

In order to gain further understanding of the role of complexity of a CLO's design on the number of ratings disclosed, we examine whether issuers dealing with CRAs in disagreement, i.e., when there is a discrepancy in ratings (in such a circumstance the ratings are often called 'split'), are more likely to disclose both ratings for CLOs that are more complex than for less complex CLOs, as described in Hypothesis H3. Rating discrepancy between Moody's and S&P is measured by the number of notches difference between each rating at issuance. For example, if a security is rated Aaa by Moody's and AA+ by S&P, we calculate rating discrepancy by subtracting the numerical value of Moody's rating (1) by the numerical value of S&P's rating (2), resulting in rating discrepancy of 1.[31] Vice versa, if the security is rated AAA by S&P and Aa1 by Moody's, we also report one notch difference. In total, in our analysis we include 567 CLOs with split ratings.

Figure 3.2(a) presents a scatter-plot of the rating discrepancy in notches difference between Moody's and S&P, sorted by issuance year. The figure illustrates that rating discrepancy fluctuates across time and it is most pronounced in the period between 2004 to 2009. What we notice is that in this period issuers most frequently disclosed split ratings with a credit rating difference of one notch. In the period after 2009, we observe a dramatically lower number of split ratings and with a lower amount of notches difference. Figure 3.2(b) presents a scatter-plot of Moody's and S&P by number of notches difference. The 45-degree line is where the CLOs would fall if the CRAs would have given identical credit ratings to the CLOs at the time of their issuance.

[31] We conducted similar regression analyses with positive and negative values for rating discrepancy, with positive (negative) values if the numerical value of Moody's rating is higher (lower) than S&P. We obtained similar results, which are not reported in this paper. Results are available upon request.

In Table 3.4, we show the ordered logit tests of model (2), where we measure the impact of deal complexity characteristics on *Rating Discrepancy* between credit ratings provided by Moody's and S&P on the same CLO, including controls. In column (3), we find that a one standard deviation change in *Capital Allocation* increases the odds of experiencing an increase in notches difference by 200%, which is significant at a 5% level (ζ-stat=2.04). This result suggests that in the pre-crisis period a higher rating discrepancy between Moody's and S&P is reported when there is a higher level of capital underlying the CLO tranche. However, the sign of the coefficient changes with the inclusion of the post crisis dummy (column 6). Those CLOs that report higher capital levels after the crisis were less likely to report two ratings with a relatively high number of notches difference, with the odds of 443%, statistically significant at a 5% level (ζ-stat=-2.06). We further find that tranche count is negative and significantly related to rating discrepancy, but only at a 10% significance level. We find no significant results for *Log Tranche Size*. For completeness, the Appendix[32] presents additional ordered logit regressions to study the impact of business cycles on rating discrepancy and complexity in more detail. These findings confirm our results in Table 3.4 that more complex CLOs with a higher capital allocation are less likely to report larger split ratings between S&P and Moody's during periods of a recession, and more likely during the period after the Global Recession.

Overall, the results of Table 3.4 show that of the three complexity characteristics, capital allocation is the most significant factor that determines the size of the rating discrepancy disclosed at issuance. Whilst these findings validate capital allocation as a measure of complexity, more importantly, they do not support Hypothesis 3, i.e., our original thought that a higher CLO complexity would result in more rating discrepancy must be rejected for the period after the crisis.

[32] The table is available in Appendix I. Supplementary Table I for Chapter 3.

Table 3.2: Logit regressions of CLO complexity characteristics on the number of credit ratings reported at issuance.

This table reports logit regressions of the underlying CLO complexity components on the number of ratings, controlled for deal-level characteristics, issuer characteristics and market conditions. We use the full sample of CLO securities issued in November 1996 up to May 2013, the year in which multiple ratings became mandatory in Europe. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg. The dependent variable is the dichotomous variable 'Number of Ratings' that equals 1 if, at issuance, a security had two ratings and zero if it had only one rating. 'Tranche Count' stands for the total number of tranches in the CLO of which the security is a part of, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. 'Euro Market' is a dummy variable of 1 when the security is issued and sold in the Euro market, and zero if it is issued and sold in the US market. 'Top Ten Issuer' is a dummy that equals 1 if the issuer is among the top 10% of issuers in the global CLOs market measured by size, and zero otherwise. 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance. 'Credit Ratings' are a set of dummy variables to indicate the credit rating of a security at issuance by Moody's and/or S&P, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Year Controls' represent the year of issuance, which equals a dummy of 1 that corresponds to the year the CLO was issued, zero otherwise. 'Post' is introduced in columns (5) to (8) and used as an interaction term that equals 1 if a security is issued after 2007. We further test if the results are sensitive to modifications by rotationally removing complexity indicators in columns (2) to (4). White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel B presents results for AAA tranches only; Panel C for non-AAA tranches only.

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity Indicators								
Tranche Count	0.04***		0.00	0.07***	0.02	0.04***	0.04***	0.04***
	(3.72)		(-0.01)	(6.28)	(1.42)	(3.62)	(3.72)	(3.18)
Tranche Count**Post*					0.16***			
					(6.06)			
Log Tranche Size	0.29***	0.24***		0.35***	0.3***	0.33***	0.29***	0.29***
	(7.19)	(6.67)		(8.33)	(7.54)	(7.68)	(7.15)	(7.22)
Log Tranche Size**Post*						-0.14**		
						(-2.43)		
Capital Allocation	2.38***	2.58***	2.64***		2.35***	2.40***	2.35***	2.40***
	(9.08)	(9.87)	(9.67)		(8.91)	(9.09)	(8.09)	(8.98)
Capital Allocation **Post*							0.12	
							(0.25)	

Table 3.2: Continued

Panel A: Full Sample								
Control Variables								
Euro Market	-1.87***	-1.84***	-1.81***	-1.76***	-1.82***	-1.86***	-1.87***	-1.79***
	(-26.1)	(-26.2)	(-25.3)	(-24.7)	(-25.2)	(-25.9)	(-26.2)	(-24.0)
Euro Market**Post*								-0.58**
								(-2.38)
Top Ten Issuer	-0.26***	-0.26***	-0.25***	-0.28***	-0.29***	-0.27***	-0.26***	-0.27***
	(-4.04)	(-4.03)	(-3.92)	(-4.44)	(-4.49)	(-4.17)	(-4.04)	(-4.11)
Log Transaction Value	0.12**	0.19***	0.32***	-0.01	0.13**	0.13**	0.12**	0.14**
	(2.01)	(3.42)	(6.26)	(-0.11)	(2.21)	(2.22)	(1.97)	(2.31)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8,364	8,364	8,364	8,364	8,364	8,364	8,364	8,364
R^2	0.323	0.322	0.314	0.310	0.327	0.324	0.323	0.324

Panel B: AAA Tranches Only Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity Indicators								
Tranche Count	0.16***		0.09***	0.20***	0.14***	0.16***	0.16***	0.15***
	(5.56)		(3.52)	(6.95)	(4.71)	(5.31)	(5.24)	(5.20)
Tranche Count**Post*					0.12*			
					(1.79)			
Log Tranche Size	0.32***	0.18***		0.37***	0.32***	0.45***	0.34***	0.31***
	(5.29)	(3.85)		(5.59)	(5.36)	(5.83)	(5.32)	(5.26)
Log Tranche Size**Post*						-0.54***		
						(-5.37)		
Capital Allocation	2.26***	2.76***	2.59***		2.27***	2.52***	3.48***	2.28***
	(6.84)	(8.18)	(7.12)		(6.84)	(6.93)	(7.80)	(6.78)
Capital Allocation**Post*							-4.01***	
							(-5.11)	
Control Variables								
Euro Market	-2.01***	-1.94***	-2.00***	-1.83***	-2.00***	-2.03***	-2.10***	-1.85***
	(-13.2)	(-13.2)	(-13.2)	(-12.3)	(-12.9)	(-13.4)	(-13.5)	(-11.3)
Euro Market**Post*								-0.86**
								(-1.99)
Top Ten Issuer	-0.42***	-0.47***	-0.34**	-0.45***	-0.45***	-0.45***	-0.41***	-0.42***
	(-2.87)	(-3.25)	(-2.38)	(-3.23)	(-3.03)	(-3.07)	(-2.81)	(-2.85)
Log Transaction Value	0.00	0.24**	0.33***	-0.10	0.01	0.08	0.01	0.03
	(0.03)	(2.02)	(3.20)	(-0.83)	(0.08)	(0.69)	(0.09)	(0.28)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,641	2,641	2,641	2,641	2,641	2,641	2,641	2,641
R^2	0.272	0.251	0.247	0.244	0.274	0.290	0.289	0.275

Panel C: Non-AAA Tranches Only Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity Indicators								
Tranche Count	0.01		-0.04***	0.05***	-0.01	0.00	0.01	0.01
	(0.93)		(-3.35)	(3.71)	(-0.69)	(0.12)	(0.82)	(0.45)
Tranche Count**Post*					0.24***			
					(5.30)			
Log Tranche Size	0.40***	0.38***		0.49***	0.45***	0.64***	0.39***	0.41***
	(6.97)	(7.66)		(8.69)	(7.53)	(9.74)	(6.66)	(7.08)
Log Tranche Size**Post*						-1.31***		
						(-9.23)		
Capital Allocation	2.98***	3.08***	3.43***		2.83***	3.02***	3.41***	3.03***
	(6.40)	(7.03)	(7.25)		(6.08)	(6.21)	(6.18)	(6.34)
Capital Allocation**Post*							-2.12**	
							(-2.26)	
Control Variables								
Euro Market	-1.72***	-1.71***	-1.65***	-1.62***	-1.67***	-1.68***	-1.74***	-1.64***
	(-19.8)	(-20.0)	(-19.1)	(-19.0)	(-19.1)	(-18.9)	(-20.0)	(-18.8)
Euro Market**Post*								-0.93**
								(-2.34)
Top Ten Issuer	-0.22**	-0.22**	-0.23***	-0.26***	-0.24***	-0.27***	-0.23***	-0.23***
	(-2.58)	(-2.58)	(-2.72)	(-3.08)	(-2.86)	(-3.21)	(-2.69)	(-2.73)
Log Transaction Value	0.18**	0.21***	0.4***	0.02	0.18**	0.27***	0.20**	0.21***
	(2.43)	(3.06)	(6.12)	(0.26)	(2.35)	(3.46)	(2.56)	(2.71)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,723	5,723	5,723	5,723	5,723	5,723	5,723	5,723
R^2	0.415	0.415	0.405	0.404	0.420	0.433	0.416	0.416

Table 3.3: Logit regressions of CLO complexity characteristics on the number of credit ratings at issuance for Moody's and S&P.

This table reports logit regressions of the underlying complexity components on number of ratings controlled for deal-level characteristics, issuer characteristics and market conditions. We use the sample of CLO securities issued in November 1996 up to May 2013, the year in which multiple ratings became mandatory in Europe. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg. The dependent variable is the dichotomous variable 'Number of Ratings' that equals 1 if, at issuance, a security had two ratings and zero if it had only one rating of Moody's (Panel A) or S&P (Panel B). 'Tranche Count' stands for the total number of tranches in the CLO of which the security is a part of, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. 'Post' is introduced in columns (5), (6), (7), and (8) and used as an indicator interaction term that equals 1 if a security is issued after 2007. All other independent variables are defined in Table 3.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

Panel A: Dependent Variable: Dual Rating and Moody's Exclusively Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity Indicators								
Tranche Count	0.08***		0.03***	0.12***	0.05***	0.08***	0.08***	0.07***
	(6.11)		(2.74)	(9.30)	(3.79)	(5.66)	(5.84)	(5.05)
Tranche Count**Post*					0.26***			
					(6.29)			
Log Tranche Size	0.30***	0.20***		0.37***	0.33***	0.46***	0.30***	0.31***
	(7.09)	(5.46)		(8.74)	(7.75)	(9.06)	(7.19)	(7.26)
Log Tranche Size**Post*						-0.53***		
						(-8.92)		
Capital Allocation	2.61***	3.09***	3.05***		2.60***	2.87***	3.23***	2.68***
	(8.64)	(10.1)	(9.50)		(8.51)	(8.73)	(8.41)	(8.54)
Capital Allocation**Post*							-1.95***	
							(-3.75)	
Control Variables								
Euro Market	-1.48***	-1.44***	-1.43***	-1.36***	-1.42***	-1.47***	-1.51***	-1.30***
	(-18.4)	(-18.2)	(-17.8)	(-17.2)	(-17.5)	(-18.1)	(-18.7)	(-15.1)
Euro Market**Post*								-1.37***
								(-4.70)

Table 3.3 – Continued

Top Ten Issuer	-0.25***	-0.27***	-0.24***	-0.28***	-0.29***	-0.27***	-0.26***	-0.27***
	(-3.16)	(-3.38)	(-3.08)	(-3.52)	(-3.57)	(-3.42)	(-3.24)	(-3.31)
Log Transaction Value	0.05	0.18***	0.26***	-0.08	0.06	0.10	0.06	0.10
	(0.71)	(2.98)	(4.64)	(-1.36)	(0.84)	(1.55)	(0.96)	(1.53)
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,148	7,148	7,158	7,148	7,148	7,148	7,148	7,148
R^2	0.241	0.235	0.229	0.223	0.248	0.254	0.244	0.246

Panel B: Dependent Variable: Dual Rating and S&P Exclusively Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity Indicators								
Tranche Count	-0.01		-0.03*	0.01	-0.04**	-0.02	-0.01	0.00
	(-0.87)		(-1.95)	(0.43)	(-2.35)	(-0.97)	(-0.84)	(-0.28)
Tranche Count**Post*					0.14***			
					(4.23)			
Log Tranche Size	0.12**	0.14***		0.17***	0.15***	0.04	0.11*	0.12**
	(2.12)	(2.75)		(3.53)	(2.64)	(0.58)	(1.93)	(2.11)
Log Tranche Size**Post*						0.15*		
						(1.87)		
Capital Allocation	1.61***	1.52***	1.74***		1.49***	1.57***	0.95*	1.56***
	(3.45)	(3.56)	(3.80)		(3.21)	(3.37)	(1.82)	(3.41)
Capital Allocation**Post*							1.64**	
							(2.44)	
Control Variables								
Euro Market	-2.63***	-2.64***	-2.6***	-2.56***	-2.55***	-2.64***	-2.61***	-2.87***
	(-20.2)	(-20.4)	(-19.9)	(-19.4)	(-19.2)	(-20.2)	(-20.1)	(-19.4)
Euro Market**Post*								0.95***
								(3.14)
Top Ten Issuer	-0.19**	-0.20**	-0.20**	-0.22**	-0.22**	-0.19**	-0.19**	-0.19**
	(-2.12)	(-2.15)	(-2.19)	(-2.39)	(-2.43)	(-2.04)	(-2.12)	(-2.06)
Log Transaction Value	0.14	0.11	0.22**	0.01	0.12	0.15	0.12	0.11
	(1.38)	(1.19)	(2.51)	(0.08)	(1.20)	(1.47)	(1.15)	(1.15)
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,313	7,313	7,320	7,313	7,313	7,313	7,313	7,313
R^2	0.478	0.478	0.475	0.474	0.480	0.478	0.479	0.479

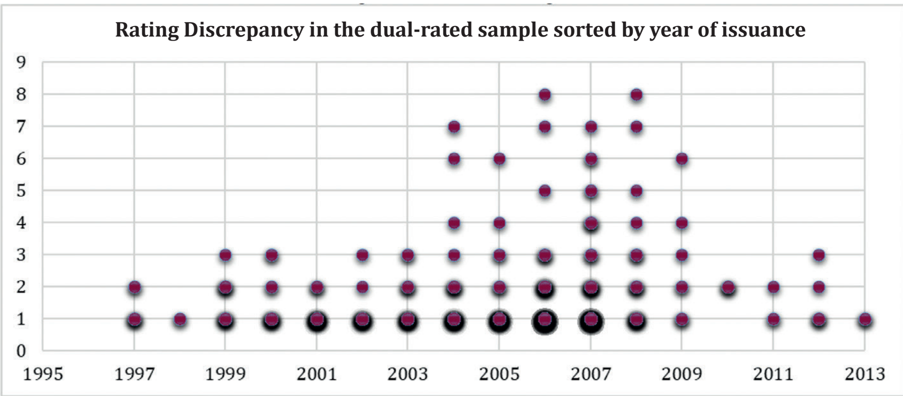


Figure 3.2 (a)

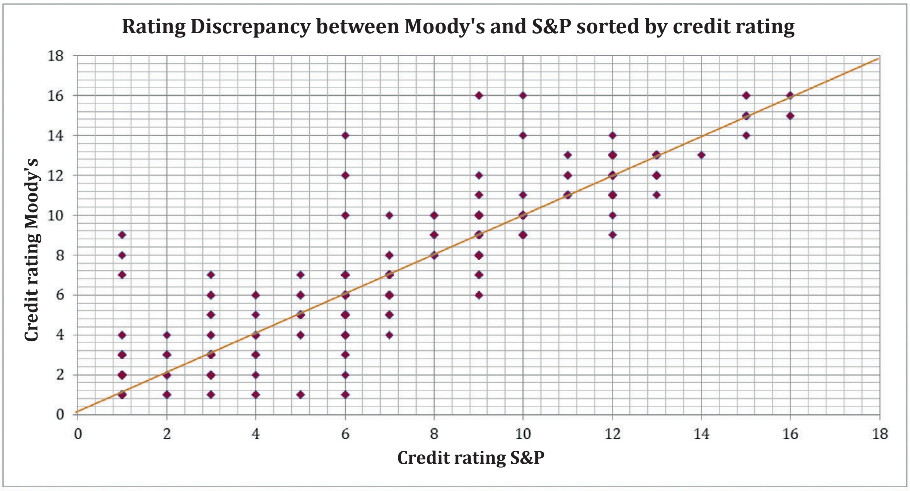


Figure 3.2 (b)

Figure 3.2: Rating discrepancy between Moody's and S&P.

This figure illustrates all tranches for which we can observe two credit ratings disclosed at issue from Moody's or S&P originated between 1996 and 2013. 'Rating Discrepancy' stands for the numerical difference between credit ratings of S&P and Moody's when each of their ratings of CLO tranches are converted to a number equivalent. Figure 3.2(a) illustrates on the y-axis the rating discrepancy in notches of Moody's and S&P, sorted on the x-axis by year of issuance. The dots with larger dark surroundings represent a higher number of tranches in the sample with rating discrepancy sorted by year of issuance and rating notch difference. Figure 3.2(b) illustrates a scatter plot of Moody's and S&P by number of notches difference. The 45-degree line is where the CLOs would fall if the CRAs would have given identical credit ratings to the CLOs at the time of issuance.

Table 3.4: Ordered logit regressions of CLO complexity characteristics on rating discrepancy for split credit ratings only.

This table reports ordered logit regressions of the underlying complexity components on the rating discrepancy between Moody's and S&P, controlled for deal-level characteristics, issuer characteristics and market conditions. This sample is based on securities that received a split rating from Moody's and/or S&P as reported on Bloomberg between 1996 and 2013, the year in which multiple ratings became mandatory in Europe. The dependent variable 'Rating Discrepancy' stands for the numerical difference between credit ratings of S&P and Moody's when their ratings are converted to numerical equivalents, for each security that has two ratings. 'Tranche Count' stands for the total number of tranches in the CLO deal of which the security is a part of, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO deal, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. 'Post' is introduced in columns (4) to (6) and used as an indicator interaction term that equals 1 if a security is issued after 2007. All other independent variables are defined in Table 3.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Complexity Indicators						
Tranche Count	-0.10**	-0.07*	-0.09*	-0.09*	-0.09*	-0.09*
	(-2.52)	(-1.89)	(-1.88)	(-1.73)	(-1.89)	(-1.76)
Tranche Count**Post*				-0.17		
				(-0.78)		
Log Tranche Size		0.31**	0.02	-0.00	0.03	0.02
		(2.54)	(0.10)	(-0.02)	(0.14)	(0.11)
Log Tranche Size**Post*					-0.05	
					(-0.17)	
Capital Allocation			2.00**	2.02**	2.01**	2.43**
			(2.04)	(2.03)	(2.07)	(2.49)
Capital Allocation**Post*						-4.43**
						(-2.06)

Table 3.4 – Continued

Control Variables						
Euro Market			-0.11	-0.10	-0.11	-0.06
			(-0.28)	(-0.27)	(-0.28)	(-0.16)
Top Ten Issuer			-0.08	-0.06	-0.07	-0.06
			(-0.20)	(-0.16)	(-0.18)	(-0.16)
Log Transaction Value			0.28	0.26	0.28	0.23
			(1.34)	(1.27)	(1.37)	(1.08)
Year effects	N	N	Y	Y	Y	Y
Credit rating effects	N	N	Y	Y	Y	Y
Observations	567	567	567	567	567	567
R^2	0.011	0.022	0.232	0.233	0.232	0.236

3.6 Investor Reliance on Credit Ratings of Moody's and S&P

As mentioned in the introduction, policy-makers have been focusing on the importance to investors of having more than one credit rating on structured finance securities due to the perception that they are all complex by nature. Whilst we show that complexity matters in the decision of issuers to report one or two credit ratings on their CLOs, the question remains whether investors are aware of the credit rating risk that rating catering behavior causes, and the extent to which they vary their yield requirements to reflect such credit rating risk. This point is illustrated as follows. Every CLO in our sample is rated by either Moody's, S&P, or both. In the absence of rating catering, there should be informational value contained in multiple ratings. If rating catering is prevalent, dual-rated securities will tend to contain no additional informational content, and therefore would have no additional explanatory power in the assessment of the yield compared to a single rated security (H4).

To test this hypothesis, we move to an OLS regression framework. For our regression analysis in Equation (3.3), the yield at issuance is the dependent variable and the credit rating is the key independent variable, sorted by year and issuer fixed effects. Columns (1) and (2) of Panel A in Table 3.5 contain the full sample; the single rated tranches rated exclusively by Moody's are in columns (3) and (4), the single rated CLOs rated exclusively by S&P are in columns (5) and (6), and the dual rated tranches are in columns (7) and (8). We are interested in the impact of the credit rating on the yield for securities that received one or two credit ratings and the explanatory value as measured by R^2. Column (1) does not include any control variables. The R^2 of 0.52 reveals a significant explanatory power of the credit rating. Columns (3) and (5) show that the credit rating coefficient is dramatically lower for a CLO that is rated exclusively by Moody's, with a coefficient of 18.19, compared to 32.57, in column (5), for a CLO that is rated solely by S&P. Also, in columns (3) and (5), we see for CLOs exclusively rated by S&P a R^2 of 0.55, almost twice the size of the explanatory power of our model results for Moody's only, where we see a R^2 of 0.29. These findings are robust for CLO controls like vintage, time and issuer fixed effects. Moreover, looking at the credit rating coefficient of dual rated CLOs in column (7), we see a coefficient of 30.67, which is even lower than the value for the same coefficient for a CLO that is rated only by S&P. Looking at the R^2 in both columns one can also see that the explanatory power of dual rated CLOs is not significantly different than the R^2 for CLOs rated by S&P alone. It therefore appears that, in a deal rated by S&P, investors do not significantly rely on the additional information content of a rating by Moody's in their assessment of the required yield for the CLOs.

Our results in Panel A of Table 3.5 firstly suggest that investors do rely on CRAs in their risk assessment of the required yield, but they clearly differentiate between CRAs. Secondly, our results suggest that investors seem to perceive more credit rating risk with Moody's compared to S&P, and as a result they seem to rely substantially less on a Moody's credit rating compared to S&P.

Panel B of Table 3.5 repeats Panel A, but shows the regression results when we compare and contrast the pre-crisis and post-crisis periods. Similar to the previous results, the coefficient of the credit rating for CLOs exclusively rated by Moody's in column (1) is substantially lower than CLOs exclusively rated by S&P in column (3). The same observations as set out regarding Panel A apply to the explanatory power. Note that post-crisis, the credit rating coefficient for CLOs rated by S&P remains at the same level of roughly 32 in the pre-crisis period, while Moody's credit rating coefficient drops dramatically with about 50% from 24 in column (1) pre-crisis to 12 in column (2) post-crisis. Clearly, the credit rating provided by Moody's has substantially less impact compared to S&P in the assessment of the required yield by investors. However, post-crisis we see that dual ratings with a coefficient of roughly 42 in column (6) have a larger explanatory power than before the crisis with a coefficient of 35 in column (5).

If we move to the complexity indicators in Panel B of Table 3.5 in the post-crisis period (column 6), we notice that dual credit ratings not only have a dramatic higher coefficient for credit rating, the significance of the complexity factors has disappeared entirely compared to pre-crisis in column (5). These results suggest that investors on average perceive that there is additional risk in deal complexity beyond the credit rating pre-crisis, but not after the crisis.

In sum, before the crisis our findings support Hypothesis 4 that on average dual ratings do not have greater information value in the determination of the required yield than a single rated tranche, albeit only for S&P. After the crisis, we see an opposite effect, where CLOs with dual ratings have a greater explanatory power compared to CLOs with a single rating. However, we show that the explanatory power is substantially stronger in the presence of an S&P credit rating than in the presence of a rating by Moody's, before and after the crisis. Whilst an S&P credit rating remains key to investors in CLOs for determining their yield requirement, prior to the crisis the addition of Moody's did not substantially influence their yield requirements, whereas post-crisis it did.

Table 3.5: OLS regression of yield spread to underlying CLOs characteristics.

This table reports OLS regressions of the yield spread (at issuance) of CLOs on the underlying complexity components, controlled for deal-level characteristics, issuer characteristics and market conditions. We use the sample of CLO securities issued in November 1996 up to May 2013, the year in which multiple ratings became mandatory in Europe. The sample is based on securities that received a rating from Moody's and/or S&P as reported on Bloomberg. The dependent variable is the primary issuance spread 'Spread', measuring the quoted margin between the benchmark rate and the coupon of the initial yield, measured in basis points. 'Tranche Count' stands for the total number of tranches in the CLO of which the security is part of. 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. All other independent variables are defined in Table 3.2. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for the full, single and dual rating sample. Columns (1) and (2) present the results for the full sample, columns (3) and (4) for the tranches rated by Moody's exclusively, columns (5) and (6) for tranches rated by S&P exclusively, and columns (7) to (8) for the dual rated tranches. Panel B divides the single and dual rating sample in pre- and post-crisis periods. Columns (1) and (2) present the pre- and post-crisis results for the sample of tranches rated by Moody's exclusively, columns (3) and (4) for the sample of tranches rated by S&P exclusively, and columns (5) and (6) for the dual rating sample.

Panel A: Full, Single, and Dual Rating Sample

	Full sample		Moody's exclusively		S&P exclusively		Dual Rating Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Rating	30.03***	30.21***	18.19***	17.22***	32.57***	31.06***	30.67***	34.92***
	(63.37)	(55.62)	(14.76)	(13.09)	(34.32)	(32.85)	(58.33)	(59.51)
Complexity Indicators								
Tranche Count		1.43**		5.78*		-4.34**		0.28
		(2.22)		(1.69)		(-2.06)		(0.41)
Log Tranche Size		-2.34*		-1.85		-7.89**		4.74***
		(-1.90)		(-0.54)		(-1.98)		(4.23)
Capital Allocation		42.27***		3.65		76.54***		68.34***
		(5.26)		(0.18)		(2.59)		(8.41)

Table 3.5 – Continued

	Moody's exclusively		*S&P exclusively*		*Dual Rating Sample*	
	Pre-crisis	*Post-crisis*	*Pre-crisis*	*Post-crisis*	*Pre-crisis*	*Post-crisis*
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Rating	24.32***	11.62***	30.21***	32.18***	34.72***	41.95***
	(13.46)	(7.68)	(13.40)	(34.68)	(56.40)	(16.51)
Complexity Indicators						
Tranche Count	1.37	2.89	-6.63**	-0.17	-1.17	0.63
	(0.35)	(0.54)	(-2.04)	(-0.07)	(-1.32)	(0.38)
Log Tranche Size	5.34	0.24	5.60	-9.03*	8.37***	-6.78
	(1.23)	(0.04)	(0.88)	(-1.84)	(6.83)	(-1.64)
Capital Allocation	30.05	-87.00***	114.3***	52.80	68.41***	34.46
	(1.12)	(-2.12)	(2.65)	(1.31)	(8.35)	(0.90)
Control Variables						
Euro Market	160.8	-1.26	-166.2**	1.57	-5.16	-3.81
	(0.83)	(-0.13)	(-1.97)	(0.12)	(-0.78)	(-0.12)
Top Ten Issuer	-17.64	-96.87	-128.8	32.73	49.75*	-232.8***
	(-0.52)	(-1.42)	(-1.34)	(1.36)	(1.91)	(-3.97)

Panel B: Pre-crisis versus Post-crisis Sample

	Moody's exclusively		*S&P exclusively*		*Dual Rating Sample*	
	Pre-crisis	*Post-crisis*	*Pre-crisis*	*Post-crisis*	*Pre-crisis*	*Post-crisis*
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Rating	24.32***	11.62***	30.21***	32.18***	34.72***	41.95***
	(13.46)	(7.68)	(13.40)	(34.68)	(56.40)	(16.51)
Complexity Indicators						
Tranche Count	1.37	2.89	-6.63**	-0.17	-1.17	0.63
	(0.35)	(0.54)	(-2.04)	(-0.07)	(-1.32)	(0.38)
Log Tranche Size	5.34	0.24	5.60	-9.03*	8.37***	-6.78
	(1.23)	(0.04)	(0.88)	(-1.84)	(6.83)	(-1.64)
Capital Allocation	30.05	-87.00***	114.3***	52.80	68.41***	34.46
	(1.12)	(-2.12)	(2.65)	(1.31)	(8.35)	(0.90)
Control Variables						
Euro Market	160.8	-1.26	-166.2**	1.57	-5.16	-3.81
	(0.83)	(-0.13)	(-1.97)	(0.12)	(-0.78)	(-0.12)
Top Ten Issuer	-17.64	-96.87	-128.8	32.73	49.75*	-232.8***
	(-0.52)	(-1.42)	(-1.34)	(1.36)	(1.91)	(-3.97)
Log Transaction Value	-11.69	3.25	5.74	-22.82	-10.09	-8.61
	(-0.76)	(0.27)	(0.35)	(-1.49)	(-1.49)	(-0.46)
Year Effects	Y	Y	Y	Y	Y	Y
Issuer Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	566	468	333	1,154	4,563	622
Adjusted R^2	0.636	0.712	0.689	0.859	0.728	0.808

3.7 Conclusion

The relevance for investors' risk analysis of the number of ratings per security has received substantial attention by academics and regulators in the last decade. However, the role played by the complexity of a security's design remained unclear and the current de facto view of policy-makers is that all structured finance securities are equally complex. We use a large universe of CLO tranches rated by Moody's and/or S&P originated and sold between 1996 through 2013, the year in which the EU regulations regarding dual credit ratings for structured products came into force.

In sum, issuers of CLOs choose one or two CRAs to rate their CLO and disclose either the most favorable rating or both. There have been instances where rating shopping is likely, and instances where rating catering is likely. For investors, this means that there is credit rating risk, the risk that ratings do not fully or accurately reflect the actual credit risk of a security at issuance, by, for example, assigning biased ratings to structured products. Our results show that disclosing the number of ratings by S&P and Moody's at issuance, appears to vary with the individual complexity measures through their correlation with the business cycle. Significant indicators of CLO tranche complexity pertain to the capital structure and the size of the CLO tranches. Furthermore, notwithstanding our conclusion that CLO investors in the market do rely on credit ratings, a single S&P credit rating has substantially more impact than a single Moody's rating in pricing CLOs at issuance, both before and after the crisis. So, investors appear to spend the time, effort and money, i.e., incur the search costs, to differentiate between deals (complex or not, rated by S&P or Moody's or both) as they determine their yield requirements.

Consequently, the EU regulations that have made dual ratings mandatory for all structured finance securities (including CLOs) since 2013 may be counter-productive as a measure to improve the functioning of the market. First, investors no longer can differentiate their yield requirements for single and dual rated deals, taking away the ability of issuers to make an informed choice of the benefits versus search costs of adding a second CRA to a deal, for example, depending on whether the deal is complex or not. Second, having dual ratings as a mandatory requirement may act as an incentive to rating catering, given that in the absence of a second CRA the CLO will no longer be able to be placed in the market.

Our findings suggest that a regulatory environment that takes into account the complexity of a security's design may be more suited to effectively and efficiently regulate the market: for CLOs, only complex deals require dual ratings in the view of the investors for whom the regulations were made. Building on the US Dodd-Frank Act, our recommendation would be to require CRAs, as they rate CLOs, to report specifically on their considerations in relation to the complexity characteristics that we found to be important drivers in the determinations of the need for one or multiple ratings. In addition, if CRAs were to be required to publish (preliminary) contacts between themselves and issuers, and be required to comment on each other's ratings (even if after the fact), such disclosure will help both issuers and investors to make better-informed decisions about which CRA to engage, and about whether the CRAs are inclined to match each other ratings, so that they can take those decisions into consideration as they determine yield requirements. Based on our research, it is suggested that such requirements are to be particularly directed at securities with complex security designs.

The limitation of our study and of prior empirical literature on rating shopping and rating catering is that the underlying intention of an issuer to shop for credit ratings, or of a CRA to cater or match the rating of the other agency in a duopoly, cannot be observed. If regulations or market practices were to change, e.g., requiring disclosure of the (preliminary) contacts between CRAs and issuers, or requiring CRAs to comment on each other's ratings, further research getting closer to underlying intentions of issuers and CRAs may become possible.

Appendices

Appendix I. Supplementary Table I for Chapter 3

Table I: The impact of business cycles on split credit ratings. an ordered logit regression of rating discrepancy for split credit rating only on underlying CLO complexity components

This table reports ordered logit regressions of rating discrepancy between Moody's and S&P on the underlying complexity components, controlled for deal-level characteristics, issuer characteristics and market conditions. This sample is based on securities that received a split rating from Moody's and/or S&P as reported on Bloomberg between 1996 and 2013, the year in which multiple ratings became mandatory in Europe. The dependent variable 'Rating Discrepancy' stands for the numerical difference between credit ratings of S&P and Moody's when their ratings are converted to numerical equivalents, for each security that has two ratings. 'Tranche Count' stands for the total number of tranches in the CLO deal of which the security is a part of, 'Log Tranche Size' is the natural logarithm of the face value of the security at issuance. 'Capital Allocation' represents the level of internal credit enhancement supporting such a security within a CLO deal, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the CLO. We use the following interaction terms to test the impact of business cycles on rating discrepancy: 'Pre Dotcom' equal 1 if a security is issued before 2001, 'Dotcom' equals 1 if a security is issued in 2001, 'Pre Global Recession' equals 1 if a security is issued between 2002-2007', and 'Global Recession' equals 1 if a security is issued after 2007. All other independent variables are defined in Table 3.2 of the paper. White (1980) heteroskedasticity-adjusted t-statistics in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Complexity Indicators						
Tranche Count	-0.09*	-0.13	-0.09*	-0.09*	-0.10*	-0.10**
	(-1.76)	(-0.73)	(-1.82)	(-1.88)	(-1.92)	(-2.05)
Log Tranche Size	-0.002	0.02	0.02	0.04	0.02	-0.04
	(-0.01)	(0.08)	(0.08)	(0.14)	(0.12)	(-0.21)
Capital Allocation	2.02**	1.99**	1.82*	2.03**	2.85**	-1.61
	(2.02)	(1.99)	(1.77)	(2.06)	(2.56)	(-0.87)
Tranche Count**Global Recession*	-0.18					
	(-0.81)					
Tranche Count**Dotcom*	0.47					
	(1.33)					
Tranche Count*P*re Dotcom*		0.05				
		(0.22)				

Table I – Continued

Tranche Count**Pre Global Recession*		0.04				
		(0.20)				
Log Tranche Size**Global Recession*			-0.03			
			(-0.09)			
Log Tranche Size**Dotcom*			0.44			
			(0.94)			
Log Tranche Size**Pre Dotcom*				0.07		
				(0.17)		
Log Tranche Size**Pre Global*				-0.04		
				(-0.15)		
Capital Allocation**Global Recession*					-4.59**	
					(-2.08)	
Capital Allocation**Dotcom*					-4.07*	
					(-1.70)	
Capital Allocation**Pre Dotcom*						1.23
						(0.64)
Capital Allocation**Pre Global*						6.11***
						(3.05)
Control Variables						
Euro Market	-0.10	-0.12	-0.11	-0.11	-0.06	0.06
	(-0.26)	(-0.28)	(-0.27)	(-0.28)	(-0.16)	(0.17)
Top Ten Issuer	-0.06	-0.07	-0.07	-0.09	-0.07	-0.28
	(-0.17)	(-0.19)	(-0.17)	(-0.22)	(-0.19)	(-0.75)
Log Transaction Value	0.22	0.28	0.24	0.29	0.28	0.37*
	(1.06)	(1.35)	(1.12)	(1.38)	(1.24)	(1.68)
Year effects	Y	Y	Y	Y	Y	Y
Credit rating effects	Y	Y	Y	Y	Y	Y
Observations	567	567	567	567	567	567
R^2	0.234	0.232	0.233	0.232	0.238	0.247

References

Akins, B. (2017). Financial reporting quality and uncertainty about credit risk among ratings agencies. *The Accounting Review, 93*(4), 1–22. https://doi.org/10.2308/accr-51944

An, X., Deng, Y., Nichols, J. B., & Sanders, A. B. (2014). What is subordination about? Credit risk and subordination levels in commercial mortgage-backed securities (CMBS). *The Journal of Real Estate Finance and Economics, 51*, 231–253. https://doi.org/10.1007/s11146-014-9480-1

Arora, S., Barak, B., Brunnermeier, M., & Ge, R. (2011). Computational complexity and information asymmetry in financial products. *Communications of the ACM*, *54*(5), 101–107. https://doi.org/10.1145/1941487.1941511

Ashcraft, A., Goldsmith-Pinkham, P., Hull, P., & Vickery, J. (2011). Credit ratings and security prices in the subprime MBS market. *American Economic Review*, *101*(3), 115–119. https://doi.org/10.1257/aer.101.3.115

Baghai, R. P., & Becker B. (2018). *Reputations and credit ratings: Evidence from commercial mortgage-backed securities* [Discussion paper]. C.E.P.R. Discussion Papers 12648. https://ideas.repec.org/p/cpr/ceprdp/12648.html

Bakalyar, I., & Galil, K. (2014). Rating shopping and rating inflation in Israel. *International Review of Financial Analysis*, *33*, 270–280. https://doi.org/10.1016/j.irfa.2014.03.005

Bar-Isaac, H., & Shapiro, J. (2013). Ratings quality over the business cycle. *Journal of Financial Economics*, *108*(1), 62–78. https://doi.org/10.1016/j.jfineco.2012.11.004

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, *101*(3), 493–514. https://doi.org/10.1016/j.jfineco.2011.03.012

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, *67*, 85–111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Bongaerts, D., Cremers, K. J. M., & Goetzmann, W. N. (2012). Tiebreaker: Certification and multiple credit ratings. *The Journal of Finance*, *67*(1), 113–152. https://doi.org/10.1111/j.1540-6261.2011.01709.x

Bowe, M., & Larik, W. (2014). Split ratings and differences in corporate credit rating policy between Moody's and Standard & Poor's. *Financial Review*, *49*(4), 713–734. https://doi.org/10.1111/fire.12054

Carlin, B. I., Kogan, S., & Lowery, R. (2013). Trading complex assets. *The Journal of Finance*, *68*(5), 1937–1960. https://doi.org/10.1111/jofi.12029

Dilly, M., & Mählmann, T. (2016). Is there a "boom bias" in agency ratings? *Review of Finance*, *20*(3), 979–1011. https://doi.org/10.1093/rof/rfv023

Dimitrov, V., Palia, D., & Tang, L. (2015). Impact of the Dodd-Frank Act on credit ratings. *Journal of Financial Economics*, *115*(3), 505–520. https://doi.org/10.1016/j.jfineco.2014.10.012

Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013, amending Regulation (EC) No 1060/2009 on credit rating agencies, Article 8c. (2013). http://data.europa.eu/eli/reg/2013/462/oj

European Securities and Markets Authorities. (2018). *Report on CRA market share calculation.* https://www.esma.europa.eu/sites/default/files/library/cra_market_share_calculation_2018.pdf
Fabozzi, F. J., Nawas, M. E., & Vink, D. (2017). Exploring rating shopping for European triple a senior structured finance securities. *Finance Research Letters*, *20*, 35–39. https://doi.org/10.1016/j.frl.2016.08.013
Fahad, N. U., & Laura, M. L. (2017). Complexity in structured finance and difficulties faced by market participants - A critical assessment of the role of the complexity in financial crisis. *Asian Economic and Financial Review, 7*(9), 907–920. https://doi.org/10.18488/journal.aefr.2017.79.907.920
Flynn, S., & Ghent, A. (2018). Competition and credit ratings after the fall. *Management Science, 64*(4), 1477–1973. https://doi.org/10.1287/mnsc.2016.2604
Furfine, C. H. (2014). Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies*, *2*(2), 154–187. https://doi.org/10.1093/rcfs/cft008
Ghent, A. C., Torous, W. N., & Valkanov, R. I. (2019). Complexity in structured finance. *The Review of Economic Studies*, *86*(2), 694–722. https://doi.org/10.1093/restud/rdx071
Golan, L., Parlour, C. A., & Rajan, U. (2014). Competition, managerial slack, and corporate governance. *Review of Corporate Finance Studies*, *4*(1), 43–68. https://doi.org/10.1093/rcfs/cfu011
Griffin, J. M., & Tang, D. Y. (2012). Did subjectivity play a role in CDO credit ratings? *The Journal of Finance*, *67*(4), 1293–1328. https://doi.org/10.1111/j.1540-6261.2012.01748.x

Griffin, J. M., Nickerson, J., & Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *Review of Financial Studies*, *26*(9), 2270–2310. https://doi.org/10.1093/rfs/hht036
Güntay, L., & Hackbarth, D. (2010). Corporate bond credit spreads and forecast dispersion. *Journal of Banking & Finance*, *34*(10), 2328–2345. https://doi.org/10.1016/j.jbankfin.2010.02.019
Haan, J. de, & Amtenbrink, F. (2011). *Credit rating agencies* [Working paper]. DNB Working Paper No. 278. https://doi.org/10.2139/ssrn.1760951
He, J., Qian, J., & Strahan, P. E. (2011). Credit ratings and the evolution of the mortgage-backed securities market. *American Economic Review*, *101*(3), 131–135. https://doi.org/10.1257/aer.101.3.131
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. *The Journal of Finance*, *67*(6), 2097–2137. https://doi.org/10.1111/j.1540-6261.2012.01782.x
He, J. J., Qian, J. Q. J., & Strahan, P. E. (2016). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067
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. https://doi.org/10.1007/s10693-006-0420-y

Jiang, J. X., Wang I. Y., & Wang, K. P. (2018). Revolving rating analysts and ratings of MBS and ABS: Evidence from LinkedIn. *Management Science 64*(12), 5461-5959. https://doi.org/10.1287/mnsc.2017.2921

Kiesel, F. (2016). Do investors still rely on credit rating agencies? Evidence from the financial crisis. *The Journal of Fixed Income*, *25*(4), 20–31. https://doi.org/10.3905/jfi.2016.25.4.020

Kraft, P. (2015). Do rating agencies cater? Evidence from rating-based contracts. *Journal of Accounting and Economics*, *59*(2–3), 264–283. https://doi.org/10.1016/j.jacceco.2014.09.008

Livingston, M., Naranjo, A., & Zhou, L. (2007). Asset opaqueness and split bond ratings. *Financial Management*, *36*(3), 49–62. https://doi.org/10.1111/j.1755-053x.2007.tb00080.x

Moreira, F., & Zhao, S. (2018). Do credit ratings affect spread and return? A study of structured finance products. *International Journal of Finance & Economics*, *23*(2), 205–217. https://doi.org/10.1002/ijfe.1612

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *American Economic Review*, *92*(4), 874–888. https://doi.org/10.1257/00028280260344506

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053

Sangiorgi, F., Sokobin, J. S., & Spatt, C. S. (2009). Credit-rating shopping, selection and the equilibrium structure of ratings. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1363899

Sangiorgi, F., Sokobin, J., & Spatt C. S. (2009). *Credit-rating shopping, selection and the equilibrium structure of ratings* [Unpublished manuscript]. Frankfurt School of Finance & Management. https://doi.org/10.2139/ssrn.1363899

Sangiorgi, F., & Spatt, C. (2017). Opacity, credit rating shopping, and bias. *Management Science*, *63*(12), 4016–4036. https://doi.org/10.1287/mnsc.2016.2558

Securities and Exchange Commission. (2018). *Annual Report on Nationally Recognized Statistical Rating Organizations.* https://www.sec.gov/2018-annual-report-on-nrsros.pdf

Skreta, V., & Veldkamp, L. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, *56*(5), 678–695. https://doi.org/10.1016/j.jmoneco.2009.04.006

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817. https://doi.org/10.2307/1912934

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: Rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Chapter 4

Intensified Competition and The Impact on Credit Ratings in the RMBS market

Financial Markets, Institutions & Instruments, 2023,
DOI: 10.1111/fmii.12170

Vivian M. van Breemen
Frank J. Fabozzi
Dennis Vink

Acknowledgement: *We thank Markus Brunnermeier and Laura Starks for the invitation to participate in the American Finance Association Conference 2022. We also thank the Editorial Board of the European Central Bank (ECB) Working Paper Series for their review and invitation to publish in the ECB Working Paper Series. Disclaimer: This paper should not be reported as representing the views of the ECB. The views expressed are those of the authors and do not necessarily reflect those of the ECB.*

Abstract

In this paper, we empirically investigate the impact of intensified competition on rating quality in the credit rating market for residential mortgage-backed securities (RMBS) in the period 2017-2020. We provide evidence that competition between large credit rating agencies (CRAs) (Moody's and Standard & Poor's) and newer smaller ones (Dominion Bond Rating Service Morningstar and Kroll Bond Rating Agency) creates credit rating inconsistencies in the RMBS market. While a credit rating should solely represent the underlying credit risk of a RMBS, irrespective of the competition in the market, our results show that this is not the case. When competitive pressure is higher, both large and small CRAs tend to adjust their rating standards (smaller CRAs react to large CRAs and vice versa).

Keywords: rating quality, credit rating agencies, competitive pressure.

JEL classifications: G15, G21, G24, G28.

4.1 Introduction

The credit rating agencies (CRAs) and those identified as producers of credit ratings in the United States (US) are referred to as national recognized statistical organizations. The credit rating market continues to be dominated by three major players – Moody's, Standard & Poor's (S&P), and Fitch – who assigned 92% of the credit ratings in the European Union (EU) and 95% in the US market (ESMA, 2020; SEC, 2020). This triopoly in combination with the way revenue is generated (i.e., issuer-pays revenue model) in the credit rating industry is one of the problems that critics of CRAs argue caused inflated credit ratings (see e.g., Bolton et al., 2012; Goldstein and Huang, 2020).[33,34]

However, the new rules and regulations[35] in the last decade created to stimulate competition in the residential mortgage-backed securities (RMBS) market, have actually led to stronger competition and a more level playing field amongst CRAs. Smaller CRAs (e.g., Dominion Bond Rating Service Morningstar (DBRS) and Kroll Bond Rating Agency (KBRA)) have gained prominent market shares at the expense of S&P, Fitch, and Moody's in the RMBS market. As a result, we are interested to learn to what extent intensified competition between new and traditional CRAs has impacted the quality of the RMBS ratings. Thus, in this paper we focus on the RMBS market for two reasons. First, the entry of smaller CRAs (DBRS and KBRA) to the credit rating market for RMBS offers a unique setting to empirically assess how intensified competition affects the rating quality of small and large CRAs.

[33] The income of CRAs is generated from issuers, rather than investors, while at the same time it is in the issuer's own interest to engage the rating service of the highest credit rating to optimize the issue price, or equivalently, to obtain the lowest funding cost. Issuers can request multiple credit ratings from several CRAs and select only those to their liking, while the discarded CRAs only receive a minor contract-breaking fee.

[34] That issuers are able to request and select a rating from several CRAs is argued as a conflict of interest as it motivates CRAs to grant better ratings compared to their competitors, to increase the probability that their preliminary rating will be selected by the issuer.

[35] These regulations as they pertain to CRAs include the European Union, Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on credit rating agencies, and the Regulation (EU) No 2017/2402 of the European Parliament and of The Council of 12 December 2017 on securitization of 2017. The major US regulation is the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.

Second, the RMBS market is, because of its role in the subprime mortgage crisis, one of the few markets targeted heavily by regulation where regulators sought to improve the market structure by stimulating competition and transparency in the rating process.[36]

To the best of our knowledge, our study is the first to analyze the intensified competition in a market heavily targeted by regulation, where smaller CRAs have gained significant prominence after the 2007 subprime mortgage crisis. Surprisingly, given that the objectives of rating regulation were to improve competition in the rating market for RMBS and to improve the ratings process, no studies have investigated this issue. There have been studies on various issues related to the contribution of RMBS ratings to the subprime mortgage crisis and the subsequent Global Financial Crisis (GFC), as well as other developments in the rating markets. However, previous studies that have analyzed the entry of new CRAs to the market focused mainly on bond rating developments both prior to and right after the GFC (e.g., Bae et al., 2019; Becker and Milbourn, 2011), but not on securitized products. Moreover, when competition was the focus of the rating study, the analysis primarily compared the competition of the largest two CRAs (Moody's and S&P), to that of the third largest CRA (Fitch) in the rating market for bonds (see e.g., Jewell and Livingston, 2000; Becker and Milbourn, 2011; Bae et al., 2015). Only a few studies (Flynn and Ghent, 2017; Bae et al., 2019) have scrutinized the entry of significant smaller CRAs to the credit rating market, but again not for RMBS specifically. Based on their empirical evidence, the results of competition were mixed. Becker and Milbourn (2011), for example, find economically modest but statistically significant evidence of rating inflation by Moody's and S&P in response to the entry of Fitch to the

[36] DBRS has grown to be the fourth largest international CRA, but still has only a small portion (roughly 3%) of the EU and US credit rating market as of 2020. However, DBRS' market share in the MBS market is remarkably higher. In the EU MBS market, DBRS' market share is roughly 14% as of 2020. In the US MBS market, DBRS is also the fourth largest CRA with a 2020 market share of 32%. KBRA is slightly smaller than DBRS with a total market share of 0.3% in the EU and 0.7% in the US rating market as of 2020. KBRA is the seventh largest CRA in the EU MBS market with a market share of 0.3%, while KBRA is the second largest CRA in the US MBS market with a 2020 market share of 52% (ESMA, 2020; SEC, 2020). ESMA only reports market share information at the market level (structured finance); the SEC reports more detailed information at the product-type level, but only for MBS in general. The market share in the US MBS market reported by SEC exceed 100% because more ratings per product might be assigned. The calculations by the SEC in 2020 are based on the first six months only.

credit rating market between 1997 and 2007, while Bae et al. (2015) find no relation at all between Fitch's market share and rating inflation in the period 1995-2006. In a later study covering the period 1996 to 2012, Bae et al. (2019) conclude that the ratings of DBRS for Canadian corporate bonds do become better compared to S&P's rating, when the competition (expressed by market share) of S&P intensifies. They argue that the potential risk, that is reputational damage associated with issuing better ratings, is not an effective deterrent for small CRAs. In line with Bae et al. (2019), Flynn and Ghent (2018) show that small CRAs are more likely to issue better ratings than large CRAs, particularly for interest-only tranches in the commercial mortgage-backed securities (CMBS) market in the period 2009-2014.

We use a complete dataset from Bloomberg, of 7,719 RMBS tranches, originated and sold from the first quarter of 2017 to the third quarter of 2020. The total par value of these tranches is $3 trillion. We obtained information on the underlying tranche and deal characteristics. Furthermore, we calculate the market shares of CRAs in the RMBS market and use this as a measure of competition intensity. We obtained information on credit ratings of Moody's, S&P, Fitch, DBRS, and KBRA, and use DBRS and KBRA as representatives of small CRAs and Moody's, S&P, and Fitch as the large, global CRAs. We analyze if higher market share of large (small) CRAs tend to impact the quality of ratings of small (large) CRAs. Rating quality issues arise when a CRA tends to report better or worse credit ratings, on average, than its peer, for the same tranche.[37]

In our first set of tests, we have analyzed whether higher market share of large (small) CRAs has led the smaller (larger) CRAs to assign better ratings. We find mixed results. Only for tranches rated by both Moody's and KBRA, a higher market share of Moody's has led KBRA to assign better ratings. Looking at DBRS, our results show again the strongest significance in combination with Moody's.

[37] These differences might also be caused by (unintentional) methodological errors of CRAs. However, this would not result in structural rating differences (see, e.g., Skreta and Veldkamp, 2009).

However, the results are opposite of what we would expect. In general, DBRS does not assign better ratings for the same tranche when competition of Moody's intensifies. On the contrary, our results show that in these cases Moody's reports the better ratings, not DBRS. When the situation is the other way around, so DBRS has a higher market share, it is DBRS who ends up in the deal providing the better rating and Moody's the worse one for the same tranche.

In our second set of tests, we investigate whether higher market share of large (small) CRAs has led the smaller (larger) CRAs to adjust their rating standards. We find that they do, and provide evidence that when competitive pressure is higher, both large and small CRAs tend to adjust their rating standards. In our third, and final, set of tests we examine whether small CRAs tend to provide better ratings, on average, when dealing with a more powerful issuer. We find that they do. Particularly KBRA tends to report better ratings when dealing with larger, more powerful, issuers.

Our study contributes to a growing body of literature on competition (Bolton et al., 2012; Zhou et al., 2017; Baghai and Becker, 2020) and rating standards (see e.g., Alp, 2013; Cafarelli, 2020) in the credit rating market. The works closest in spirit to our paper are those of Flynn and Ghent (2018) and Bae et al. (2019). Our paper contributes to the literature by analyzing a unique market setting, namely one in which small CRAs have gained significant prominence in the RMBS market over the past years. We are therefore able to assess whether the rules and regulations that have stimulated competition in the credit rating market are also beneficial in practice for the quality of ratings. Additionally, our paper is the first to test if small CRAs are more sensitive to issuers' power than large CRAs, building upon the work by He et al. (2012) who show that investors differentiate between the power of issuers. Our results are relevant to policymakers seeking to improve the effectiveness and efficiency of their legislative frameworks for fostering competition in the market for credit ratings.

The paper proceeds as follows. Section 4.2 reviews the related literature. Section 4.3 describes our dataset and variable construction and Section 4.4 sets forth our empirical strategy. Section 4.5 contains our analysis and the main empirical results. Section 4.6 summarizes our findings.

4.2 Literature Review

The GFC that started in the second half of 2007 was caused by an overextension of mortgages to weak borrowers (so-called subprime mortgages) which were packaged and sold to investors. It is alleged in numerous lawsuits by investors that tranches of subprime RMBS had inflated credit ratings, resulting in overpricing of these securities since investors were led to believe that they had lower credit risk.[38] What followed was a market meltdown when mortgage rates increased, which resulted in high default rates among homeowners (particularly in the case of subprime mortgages) who had adjustable-rate mortgages in 2007-2008 and faced a "mortgage payment shock" (see e.g., Richardson and White, 2009). In turn, the value of homes declined, leading to a further increase in the default rate due to what is best described as "strategic defaults".[39] It is alleged that this chain of events led to the subprime mortgage crisis and the subsequent Great Recession of 2008 was primarily attributable to inflated credit ratings assigned by CRAs and these inflated credit ratings were due to competition and the business model in the industry (He et al., 2015). The substantial losses in the RMBS market have caused major reputational damages for securitized products; investor demand dropped significantly, and regulators implemented more and stricter rules and regulations after the GFC.

[38] The increased complexity of securities made it rather difficult for investors to assess the underlying credit risks of RMBS. Consequently, they appeared to rely more heavily on risk assessments by external parties such as CRAs or trustees. For example, Deku et al. (2019) show that the reputation of trustees (those nominated to protect investor's interest) was considered more important by investors during the GFC, when risk assessments became more complex.

[39] A strategic default occurs when a homeowner finds that the market value of the property is less than the remaining mortgage balance.

The primary reason cited for CRAs to inflate credit ratings for RMBS is the way that revenue is generated by CRAs: the issuer-pays revenue model. This model means that the revenue of CRAs is not generated from investors but rather from issuers, notwithstanding that at the same time the CRA's task is to objectively rate the securities issued by these issuers in order for investors to rely on these ratings.[40] It might therefore be in the issuer's own interest to select the better ratings and, consequently, CRAs might have an incentive to cater ratings to issuer's demand (see, e.g., Griffin et al., 2013; He et al., 2015; Zhou et al., 2017; Flynn and Ghent, 2018). Empirical studies investigating the CRA rating process emphasize that CRAs are even more likely to offer better ratings if the issuer is able to bring, or possibly remove, future deals to the CRAs (see e.g., He et al., 2012). Furthermore, CRAs tend to offer better ratings when competition in the CRA market intensifies.

There is a well-established strand in the literature pertaining to competition in the CRA market. For example, studying the entry of new CRAs in the structured finance market, Flynn and Ghent (2018) find that small CRAs assign better ratings, often by several notches, than larger CRAs. They conclude that the better ratings by smaller CRAs is a strategy to win business from larger CRAs. Similarly, in their study of the Canadian bond market between 1996 and 2012, Bae et al. (2019) find that DBRS assigns more favorable, but less informative, credit ratings when S&P's competition is higher. The findings of Becker and Milbourn (2011) complement those of Bae et al. (2019), as they find that an increase in competition from Fitch results in lower rating quality assigned by the larger CRAs. Specifically, Becker and Milbourn find that an increase in Fitch's market share is predicted to increase the average credit rating of large CRAs. Morkoetter et al. (2017), however, find no evidence that CRAs assign biased ratings to tranches in order to gain market share.

[40] Before the introduction of the photocopier, investors paid for a book produced by a CRA that provided ratings. This was the investor-pays model. With the introduction of the photocopier, the credit ratings in the book could be distributed to other investors who do not need to pay for the cost of the book.

Although it might sound attractive to provide better credit ratings to gain current revenue, it does not go without the risk of losing reputation. Investigating the reputational damage to S&P in their rating of commercial mortgage-backed securities (CMBS), Baghai and Becker (2020) find that CRAs can still regain market share even if they suffered from reputational damage by issuing better ratings.[41] It seems investors in structured products tend to be forgiving in dealings with CRAs. Bae et al. (2019) state that small CRAs are more likely to forgo their reputation at the expense of future revenue than large CRAs as they have a higher immediate need to protect or gain market share, unlike large CRAs who have more to lose from a damaged reputation. After all, recovering from reputational damage is expensive, burdensome, and time-consuming.

Empirically investigating the trade-off between future income and current income of CRAs, Camanho et al. (2020) find that CRAs are more likely to provide better ratings in a monopoly than in a duopoly. They also suggest that lower entry barriers in the CRA market might increase the level of rating inflation. Similarly, Manso (2013) shows that an increase in competition results in a higher number of defaults, leading to rating downgrades. Notwithstanding the argument that competition might reduce rating quality, competition may also enhance the effectiveness of the market (Hörner, 2002). Specifically, it has been argued that competition among CRAs creates benefits such as less misreporting (Rabanal and Rud, 2017). One of the possible effects of the issuer-pays revenue model is the adjustments, and specifically loosening, of rating standards by CRAs. There are a good number of studies that have examined the quality of rating standards (see, for example, Becker and Milbourn, 2012; Alp, 2013), especially after the large number of mispriced securities that came to light during the GFC. These CRA scandals have resulted in several (forced) adjustments in rating standards by CRAs. For example, in 2009, S&P announced that it was adjusting its rating methodology for certain structured products (such as collateralized debt obligations and RMBS).

[41] These credit ratings are not only used by investors but also by regulators in the United States and European national competent authorities such as bank and insurance regulators to determine capital requirements (see White, 2010).

To summarize, the market for credit ratings has had high barriers to entry because it is largely dominated by only three players who have a well-established reputation and an international client base. As an entry strategy, a new, significantly smaller CRA might loosen its rating standards and provide more favorable ratings than its competitor to gain market share. On the one hand, large CRAs are found to be less likely, compared to smaller CRAs, to compromise their rating standards because building reputational capital is costly and recovering from a damaged reputation is a lengthy and difficult process. On the other hand, it might well be that the larger CRAs react upon the entrance of the smaller CRA and adjust their ratings compromising their standards. The possible tweaking of ratings in order to gain or retain market share is found to be even more pronounced when CRAs are dealing with powerful issuers who are able to bring potential future revenue.

4.2.1 ***Hypotheses***

Our assessment of the literature on competition in the credit rating market leads us to formulate several hypotheses regarding the ratings for RMBS products. The starting point is that the competition in the CRA market may cause it to provide better ratings to cater to the demand by issuers. We start by comparing the credit ratings of large and small CRAs for the same tranche in a given RMBS transaction. Looking at the effects of the issuer-pays revenue model, one might expect that CRAs with lower market share, such as DBRS and KBRA (*small CRA* hereafter), need to compete more aggressively (for example, by providing more favorable ratings) than CRAs who have a high market share and strong global outreach, such as Moody's, S&P, and Fitch (*large CRA hereafter*) (see, for example, Flynn and Ghent, 2018; Bae et al., 2019). We hypothesize that small CRAs are more likely to provide better credit ratings if the additional rating is assigned by a CRA that has dominant market power. We exploit these variations and test whether more competition (market share) of a large CRA in a specific market incentivizes small CRAs to provide better ratings than the large CRA, on average, for the same tranche. Hence, higher or lower market share of a larger competitor might negatively affect the rating quality of small CRAs. We construct the following hypothesis to test if competition has an impact on the rating differences between CRAs:

> *H1A. With higher competitive pressure from **large** CRAs, **small** CRAs tend to report more favorable ratings than large CRAs for the same tranche.*

We then turn to the question of how more competition (market share) from small CRAs affect the rating of larger CRAs. This is a question that is specifically of interest for the RMBS market, where the smaller CRAs recently gained significant market share. This gives us our next hypothesis:

> *H1B. With higher competitive pressure from **small** CRAs, **large** CRAs tend to report more favorable ratings than small CRAs for the same tranche.*

Extending this hypothesis, one might expect that small (large) CRAs tend to loosen their rating standards to a greater extent than large (small) CRAs and assign better ratings to retain or gain market share (irrespectively of whether the tranche received another credit rating). This leads to our next two hypotheses to test if CRAs loosen or tighten their credit rating standards with higher competition:

> *H2A: **Small** CRAs are more likely to loosen their rating standards when the competitive pressure from **large** CRAs is higher.*

> *H2B: **Larg**e CRAs are more likely to loosen their rating standards when the competitive pressure from **small** CRAs is higher.*

The issuer-pays revenue model of CRAs creates high bargaining power for issuers as they are able to solicit ratings from multiple CRAs and only disclose the ratings provided by the most favorable one(s). This bargaining power might even be higher when the issuer is able to bring many deals to the CRA market (e.g., see He et al., 2012). We expect that issuers who bring more deals to the market (large issuers hereafter) will receive and disclose better ratings than issuers who are smaller (small issuers hereafter). We expect that this effect is even more pronounced for small CRAs as they are willing to compromise their standards for the purpose of potentially generating greater revenue from prospective work offered by the large issuer. This leads to our last hypothesis:

> *H3A: Tranches issued by large issuers receive more favorable ratings from* ***small*** *CRAs, compared to large CRAs for the same tranche.*

4.3 Data

We manually collected the data for this study from *Bloomberg.* The complete universe consists of 7,119 tranches from 1,404 RMBS deals with a total value of USD 3.026 trillion that were issued and sold in the EU and US from the first quarter of 2017 to the third quarter of 2020. Using data of the most recent years allows us to study the impact of small CRAs, as they only gained significant market shares during that time period. For each deal, the dataset provides the available deal and tranche names, issuers characteristics, pricing date, reference rates, credit ratings, and principal balance.

The credit ratings in our dataset are assigned by Moody's, S&P, Fitch, DBRS, and KBRA. We apply several filters to our dataset, removing tranches with incomplete information. By including only tranches with credit rating, year of issuance, and issuer information, our sample is reduced from 7,119 to 4,211. We further discarded all tranches with missing coupon values (14 tranches) and tranche size (73 tranches). The remaining 4,190 tranches constitute our *full sample*.

4.3.1 **Dependent Variables**

To test hypothesis 1, we use the rating difference between small and large CRAs as our dependent variable. We measure the rating difference by subtracting the numerical credit rating score of a small CRA from the numerical credit rating score of a large CRAs. We create a numerical scale by converting the credit ratings to numerical scores corresponding to the rating notches. Using S&P's credit rating system as an example, the numerical scores were as follows: 1 for AAA, 2 for AA+, 3 for AA, 4 for AA-, and so on.

We measure rating difference between small and large CRAs by constructing the following four variables:

- Moody's rating minus DBRS' rating for the same tranche (*Rating Differences Moody's – DBRS*),
- S&P's rating minus DBRS' rating for the same tranche (*Rating Differences S&P – DBRS*),
- Moody's rating minus KBRA's rating for the same tranche (*Rating Differences Moody's – KBRA*), and
- S&P's rating minus KBRA's rating for the same tranche (*Rating Differences S&P – KBRA*).

Table 4.1 reports the variable distribution. For all four variables, more than half of the tranches do not have any rating difference between the small and large CRAs. Interestingly, the ratings differ mostly by one notch, and this difference is largely caused by a smaller CRA that provided a better rating on average than the larger CRA. For example, of all tranches rated by both Moody's and DBRS, 57% obtained a similar rating of both CRAs and 24% obtained a better rating of DBRS. Similarly, for tranches rated by S&P and DBRS, 59% of the tranches are rated equal and in 17% of the cases, DBRS assigned a better rating as shown in Table 4.1.

Next, to test hypothesis 2, we use the numerical credit rating scores of a CRA as the dependent variable. We use the numerical credit rating score of Moody's, S&P, DBRS, and KBRA as four separate dependent variables. Table 4.2 reports the summary statistics for the total sample. Panel B of Table 4.2 shows that the full sample of 4,190 tranches consists of 42.36% of the tranches with a single rating disclosed at the time of issuance, 51.20% of tranches with a dual rating, and 4.66% of tranches with three ratings. The majority of the tranches in our sample are rated by DBRS (2,010) and KBRA (1,661), followed by Moody's (1,583) and S&P (1,018). Fitch only rated 372 tranches in our sample.

Finally, to test hypothesis 3, we use the dependent variable *Higher by Small*, defined as a dummy variable that takes the value of one if the small CRA assigned a better rating than the larger CRA, for the same tranche, and zero if the credit rating by the large CRA is equal or better. Panel C of Table 4.2 reports the distribution for the variable. A minority of the tranches (28.86%) received a better rating by the smaller CRA. The remaining tranches (71.14%) received an equal rating by the small and large CRA or a better rating by the larger CRA.

Table 4.1: Rating differences between small and large CRAs.

This table reports summary statistics of RMBS tranches issued in the first quarter of 2017 up to the third quarter of 2020. 'Rating Differences Moody's – DBRS' stands for the numerical value of Moody's rating minus the numerical value of DBRS' rating. We have converted the credit ratings at issuance for each tranche into a numerical value, using Moody's as an example the values are: 1 for AAA, 2 for AA+, 3 for Aa, and so on. 'Rating Differences S&P – DBRS' stands for the numerical value of S&P's rating minus the numerical value of DBRS' rating. 'Rating Differences Moody's – KBRA' stands for the numerical value of Moody's rating minus the numerical value of KBRA's rating. 'Rating differences S&P – KBRA' stands for the numerical value of S&P's rating minus the numerical value of KBRA's rating.

	Rating Differences Moody's – DBRS		*Rating Differences S&P – DBRS*		*Rating Differences Moody's – KBRA*		*Rating Differences S&P – KBRA*	
Rating difference in notches	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
-4	0	0.00%	1	0.00%	0	0.00%	0	0.00%
-3	0	0.00%	4	1.00%	0	0.00%	0	0.00%
-2	15	2.00%	18	4.00%	6	1.00%	2	1.00%
-1	41	6.00%	41	8.00%	11	2.00%	9	4.00%
0	414	57.00%	297	59.00%	318	55.00%	139	60.00%
1	176	24.00%	84	17.00%	176	30.00%	63	27.00%
2	48	7.00%	30	6.00%	59	10.00%	17	7.00%
3	7	1.00%	12	2.00%	9	2.00%	0	0.00%
4	12	2.00%	10	2.00%	3	1.00%	0	0.00%
5	2	0.00%	5	1.00%	0	0.00%	0	0.00%
6	2	0.00%	0	0.00%	0	0.00%	0	0.00%
7	1	0.00%	0	0.00%	0	0.00%	0	0.00%
8	2	0.00%	0	0.00%	0	0.00%	0	0.00%
9	1	0.00%	0	0.00%	0	0.00%	0	0.00%
Total	721	100%	502	100%	582	100%	230	100%

Table 4.2: Summary statistics of RMBS characteristics.

This table reports summary statistics of RMBS tranches issued in the first quarter of 2017 up to the third quarter of 2020. 'MS Moody's by Frequency', 'MS S&P by Frequency' , 'MS DBRS by Frequency', and 'MS KBRA by Frequency' represent the percentage of the number of tranches rated by Moody's, S&P, DBRS and KBRA in a given year and market. 'MS Moody's by Balance', 'MS S&P by Balance' , 'MS DBRS by Balance', and 'MS KBRA by Balance' represent the percentage of total tranche value rated by Moody's, S&P, DBRS and KBRA in a given year and market. 'Tranche Count' stands for the total number of tranches in the RMBS of which the security is part of. 'Subordination Level' represent the level of internal credit enhancement supporting such a security within a RMBS, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the RMBS. 'Number of Ratings' is the number of ratings assigned to a specific tranche at issuance. 'Log Tranche Value' is the natural logarithm of the face value of the security at issuance. 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance. 'Top Ten Issuer by Balance Size' is a dummy that equal 1 is the issuer is among the top 10% of issuers in the RMBS market, measured by the value in balance size, and zero otherwise. 'Top Ten Issuer by Tranche Count' is a dummy that equal 1 is the issuer is among the top 10% of issuers in the RMBS market, measured by the number of tranches placed in the market, and zero otherwise. 'Coupon rate' is the coupon rate assigned for each tranche at issuance. 'Year' represents the year of issuance, which equals a dummy of 1 that corresponds to the year the RMBS was issued, and zero otherwise. 'Higher by Small' that equals 1 if, at issuance, a tranche received a better rating by the small CRA, and zero otherwise.

Panel A: Overall Summary Statistics

Variable	N	Mean	Median	Std	P25	P75
MS Moody's by Frequency	4,190	0.23	0.21	0.07	0.19	0.21
MS S&P by Frequency	4,190	0.16	0.15	0.10	0.11	0.16
MS DBRS by Frequency	4,190	0.30	0.32	0.06	0.30	0.35
MS KBRA by Frequency	4,190	0.26	0.30	0.10	0.27	0.31
MS Moody's by Balance	4,190	0.20	0.15	0.08	0.15	0.19
MS SP by Balance	4,190	0.17	0.18	0.08	0.11	0.20
MS DBRS by Balance	4,190	0.31	0.33	0.07	0.30	0.37
MS KBRA by Balance	4,190	0.26	0.28	0.10	0.26	0.30
Tranche Count	4,190	15.86	16.00	7.25	10.00	21.00
Subordination Level	4,190	0.44	0.46	0.34	0.08	0.73
Number of Ratings	4,190	1.59	2.00	0.61	1.00	2.00
Log Tranche Value	4,190	17.40	17.27	1.60	16.30	18.65
Log Transaction Value	4,190	21.12	21.01	0.96	20.63	21.36
Top Ten Issuer by Balance Size (in %)	4,190	0.58	1.00	0.49	0.00	1.00
Top Ten Issuer by Tranche Count (in %)	4,190	0.71	1.00	0.45	0.00	1.00
Coupon	4,190	2.60	3.00	1.67	0.64	3.89
Year	4,190	2019	2019	0.94	2018	2019
Higher by Small	4,190	0.16	0.00	0.37	0.00	0.00

Panel B: Number of credit ratings

Number of ratings per tranche

	Freq.	Percent
1	1,783	42.36%
2	2,155	51.20%
3	196	4.66%
Total	4,190	100%

Total credit ratings per CRA (irrespectively whether the tranche is rated by other CRAs)

CRA	Freq.
DBRS sample	2,010
KBRA sample	1,661
Moody's sample	1,583
S&P sample	1,018
Fitch sample	372
Total	6,644

Panel C: Variable specifications Higher by Small & Issuer Size

Higher by Small

	Freq.	Percent
1 (Higher by small)	622	28.86%
0 (Higher by large or equal)	1,533	71.14%
Total	2,155	100%

Issuer Size by Balance

	Freq.	Percent
1 (Top 10%)	1,308	60.70%
0 (Non-Top 10%)	847	39.30%
Total	2,155	100%

Issuer Size by Frequency

	Freq.	Percent
1 (Top 10%)	1,151	53.41%
0 (Non-Top 10%)	1,004	46.59%
Total	2,155	100%

4.3.2 **Independent Variables**

Our first key independent variable is the market share of CRAs. Following Becker and Milbourn (2011) and Bae et al. (2019), we use a CRA's market share of ratings as a measure of competition faced by other CRAs.[42] Consistent with these studies, we base our market share measures on our sample rather than publicly available data. We do so for two reasons. First, we are interested in the RMBS market specifically and public data only reports data on the structured finance market in general (EU) or the MBS (US) market, but not specifically for the RMBS market. Second, the market shares per product type in the US market show relatively diverse market shares between CRAs within the different type of structured finance product (i.e., for RMBS, CMBS, collateralized loan obligations, and asset-backed securities). Hence, using the market shares of the structured finance market in general might not provide an accurate measure of the RMBS market specifically.

We calculate the market share of CRAs before we apply any filters to our dataset as we are interested in the total market share for the RMBS market for each CRA. *Bloomberg* reports credit ratings of five CRAs for the RMBS tranches issued between 2017 and 2020. The credit ratings in our dataset are assigned by Moody's, S&P, Fitch, DBRS, and KBRA. We calculate the market share of CRAs per year in a specific market. We obtained RMBS tranches for the US and EU markets. We compute the market shares in two ways: (1) based on the total tranche value that has been rated by a CRA in a specific market per year (*MS by Balance*) and (2) based on the number of tranches that has been rated by a CRA in a specific market per year (*MS by Frequency*).[43]

[42] The market presence of the large CRA may vary across industries and time periods and impacts the intensity of competition for small CRAs.

[43] Our market share measure is calculated using the credit ratings assigned by CRAs at the time of issuance. In our study, we use primary market data only and therefore do not analyze data over time.

Table 4.3 reports summary statistics for our market share calculations. The market shares for each CRA measured by the principal balance is reported in Panel A of Table 4.3, and market share per frequency in Panel B of Table 4.3. In addition, we construct a variable that combines the market share per market per year of the three largest CRAs[44] (*Large CRAs by Balance Size* and *Large CRAs by Tranche Count*) and a variable that combines the market share per market per year of the two significant smaller CRAs[45] (*Small CRA by Balance Size* and *Small CRAs by Tranche Count*).

Figure 4.1 plots the market share measures reported in Table 4.3. We observe a relatively high portion of market share for KBRA in the US market but a very low to no market share in the EU market, both for market shares measured by balance size (Panel A of Figure 4.1) and tranche count (Panel B of Figure 4.1). For DBRS we observe relatively high market shares in both markets. Especially in the US market, the small CRAs have a dominant high market share (roughly 60%) compared to the larger CRAs in our sample period. This is consistent with the publicly available data, discussed in Section 4.1, that shows a significant higher market share of DBRS and KBRA in the US MBS market. While in the EU market, large CRAs remain the most dominant market players with market shares ranging between 66% and 80% in our sample period (Panel C of Figure 4.1).

Our second key independent variable is the size of issuers, used to test our third hypothesis. We measure issuer size in two ways: (1) whether they are large or small issuers measured by the value of their market share (*Issuer Size by Balance*), and (2) whether they are frequent issuers measured by the number of tranches they placed in the market (*Issuer Size by Frequency*). We measure relative size on a global basis, as opposed to measuring the top 10% of issuers within each

[44] That is the market share of Moody's + S&P + Fitch. For example, in 2017 in the EU market the market share by balance size would be calculated as: 35.14% (Moody's) + 20.53% (Fitch) + 10.53% (S&P) = 66.19%.

[45] That is the market share of DBRS + KBRA. For example, in 2017 in the EU market this would be calculated as: 0.00% (KBRA) + 33.81% (DBRS) = 33.81%.

market (i.e., the US and EU market) separately. Panel C of Table 4.2 shows that the majority of tranches in our sample are issued by relatively large issuers in terms of both principal balance size (60.70%) and frequency (53.41%).

4.3.3 **Control Variables**

We include several control variables to capture characteristics of the underlying deal, such as tranche count, capital allocation, transaction value, credit rating, and year of issuance. We report the descriptive statistics and variable distributions in Panels A to C of Table 4.2. *Tranche Count* equals the total number of tranches in a corresponding RMBS deal. In our total sample, the mean tranche count is 15.86. *Log Tranche Value* equals the natural logarithm of the face value of a tranche at issuance. The mean *Log Tranche Value* over the whole sample is 17.40. *Capital Allocation* is the level of credit support for a tranche and the mean is about 44% over the whole sample. *Log Transaction Value* equals the natural logarithm of the transaction value (i.e., the face value, at issuance, of the total RMBS of which the tranche is a part) measured in millions of US dollars. The mean *Log Transaction Value* of the sample is 21.12. *Coupon* is the coupon rate assigned for each tranche at issuance, the mean coupon rate of our full sample is 2.60%. *Number of ratings* is the number of ratings assigned to a tranche at issuance; the number of ratings range from 1 to 3 and the mean number of ratings over the whole sample is 1.59.

We also control for the market share of the issuer. We include a dummy variable, *Top Ten Issuer*, that equals one if the issuer is among the top 10% of issuers measured using the global RMBS market share, and zero if the issuer is among the remaining 90%.[46] We also control for the geographic location of the underlying collateral for each tranche (*Geography of Collateral*). If the geographic location of the underlying collateral is widespread (i.e., 40% in California and

[46] We do not include this variable to test our third hypothesis since we use the issuer size measure as an independent variable in that model.

60% in Wyoming), then the location with the majority of collateral is used as a measure of location (i.e., Wyoming). We also control for credit rating by using the numerical scale to convert all credit ratings to numerical scores, as explained in Section 4.3.1. In order to create one credit rating control variable, we had to combine the credit ratings of several CRAs.[47] Finally, we include *Year,* a control variable for the year in which the security is issued (ranging from 2017 to 2020).

[47] The number of observations is significantly reduced if we do not combine the credit ratings of different CRAs to create one control factor.

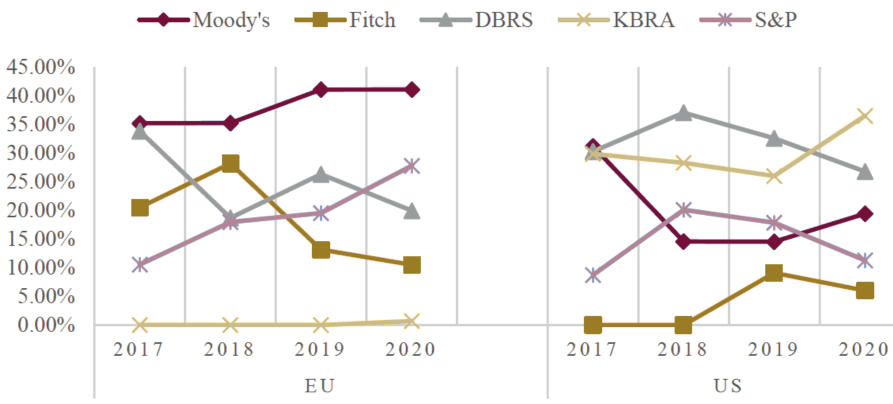


Figure 4.1(a) *Market share by balance size*

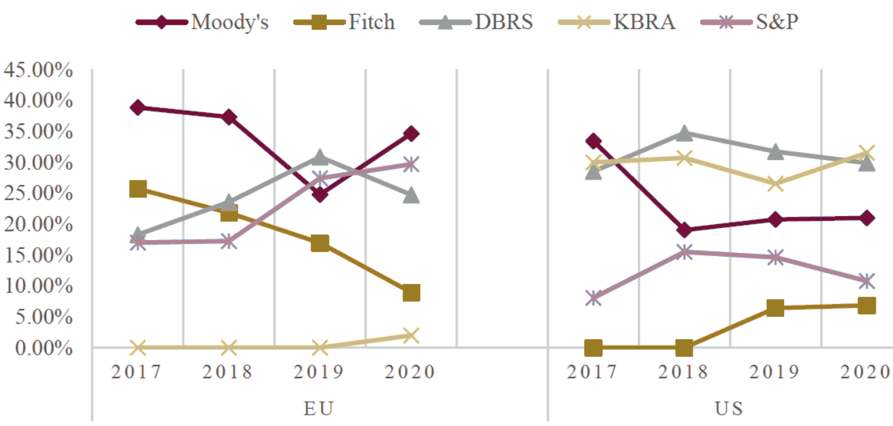


Figure 4.1 (b) *Market share by tranche count*

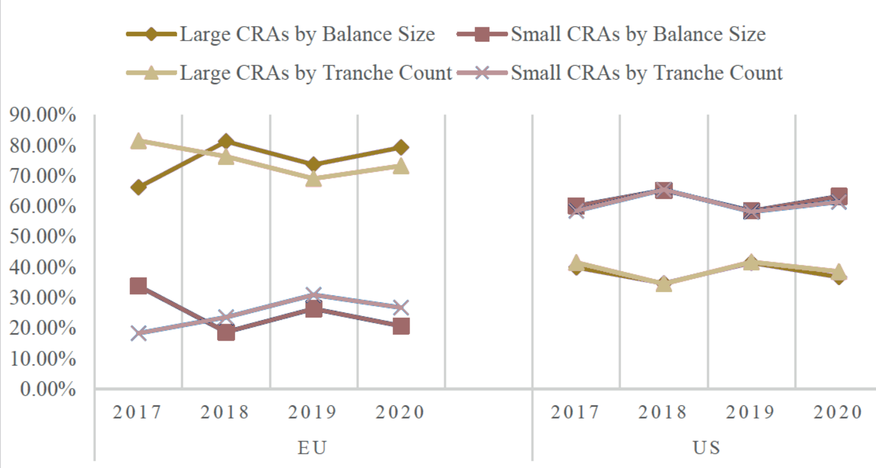


Figure 4.1 (c) *Market share: Large vs. small CRAs*

Figure 4.1: Market share of CRAs sorted by market and year.

This figure illustrates the market share movements of Moody's, Fitch, DBRS, KBRA, and S&P over time and in a specific market (the EU and US). The sample includes all tranches for which the RMBS tranche received a credit rating from one of the five CRAs disclosed at issuance originated between the first quarter of 2017 up to the third quarter of 2020. The market share percentages are set out in more detail in Table 4.3. Figure 4.1(a) illustrates the market share movements of CRAs in the RMBS market over time in a specific market, measured by balance size of a tranche. Figure 4.1(b) illustrates the market share movements of CRAs in the RMBS market over time in a specific market, measured by the number of tranches rated. Figure 4.1(c) illustrates the combined market share movements of large (Moody's, S&P, and Fitch) and small (DBRS and KBRA) CRAs in the RMBS market over time in a specific market, measured by both balance size and number of tranches rated.

Table 4.3: Market share of CRAs.

This table reports summary statistics of RMBS tranches issued in the first quarter of 2017 up to the third quarter of 2020. 'Large CRAs by Balance' stands for the combined market share, measured in terms of balance size, of Moody's, S&P, and Fitch in a given year and market. 'Small CRAs by Balance' stands for the combined market share, measured in terms of balance size, of DBRS and KBRA in a given year and market. 'Large CRAs by Frequency' stands for the combined market share, measured in terms of balance size, of Moody's, S&P, and Fitch in a given year and market. 'Small CRAs by Frequency' stands for the combined market share, measured in terms of the number of tranches rated, of DBRS and KBRA in a given year and market. All other variables are defined in Table 4.2. Panel A presents the market share calculations measured by tranche's balance size and Panel B by the number of tranches rated by a CRA in a given year and market.

Panel A: Market share of CRAs measured by Balance Size

	EU				US			
	2017	2018	2019	2020	2017	2018	2019	2020
MS Moody's by Balance	35.14%	35.21%	41.03%	41.06%	31.14%	14.59%	14.53%	19.43%
MS Fitch by Balance	20.53%	28.16%	13.14%	10.51%	0.00%	0.00%	9.08%	6.04%
MS DBRS by Balance	33.81%	18.68%	26.29%	19.95%	30.26%	37.02%	32.54%	26.76%
MS KBRA by Balance	0.00%	0.00%	0.00%	0.70%	29.86%	28.29%	25.97%	36.48%
MS S&P by Balance	10.53%	17.94%	19.54%	27.78%	8.74%	20.10%	17.87%	11.30%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Large CRAs by Balance	66.19%	81.32%	73.71%	79.35%	39.88%	34.69%	41.48%	36.76%
Small CRAs by Balance	33.81%	18.68%	26.29%	20.65%	60.12%	65.31%	58.52%	63.24%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

Panel B: Market share of CRAs measured by Tranche Count

	EU				US			
	2017	2018	2019	2020	2017	2018	2019	2020
MS Moody's by Frequency	38.86%	37.32%	24.78%	34.65%	33.44%	19.03%	20.74%	20.97%
MS Fitch by Frequency	25.71%	21.83%	16.96%	8.91%	0.00%	0.00%	6.40%	6.84%
MS DBRS by Frequency	18.29%	23.59%	30.87%	24.75%	28.54%	34.75%	31.72%	29.90%
MS KBRA by Frequency	0.00%	0.00%	0.00%	1.98%	29.96%	30.73%	26.51%	31.52%
MS S&P by Frequency	17.00%	17.25%	27.39%	29.70%	8.06%	15.49%	14.63%	10.78%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Large CRAs by Frequency	81.71%	76.41%	69.13%	73.26%	41.50%	34.52%	41.77%	38.59%
Small CRAs by Frequency	18.29%	23.59%	30.87%	26.73%	58.50%	65.48%	58.23%	61.41%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

4.4 **Methodology**

Using separate subsamples, we conduct three different tests to test our three sets of hypotheses.

First, to test hypothesis 1, we construct a subsample where we compare multiple credit ratings assigned to one tranche. Here we are interested in tranches that received a rating of at least one large and one small CRA. For this reason, we discard all tranches that received one rating (1,783) or three ratings (196) from the regressions. Unfortunately, there are an insufficient number of RMBS tranches rated by Fitch and a smaller peer (DBRS or KBRA) to enable statistical analyses on tranches rated by Fitch and a small CRA (197 tranches). This reduced our sample further to 2,035 observations, of which 721 tranches were rated by Moody's and DBRS, 582 by Moody's and KBRA, 502 by S&P and DBRS, and 230 by S&P and KBRA. The 2,035 dual-rated tranches present the first subsample used in our first model. To test hypothesis 1, we use an ordered logit model to estimate how the market share of large CRAs impact the rating quality of large and small CRAs. Our model specification to test our first hypothesis is:

$$\begin{aligned} &\textit{Rating Differences}_{jt} = \\ &\quad \alpha_0 + \alpha_1\, \textit{Market Share CRA}_{jt} + \textit{Tranche, Issuer and Market Controls}_{ijt} + \epsilon_{ijt} \end{aligned} \tag{4.1}$$

The data vary by year (t), deal (i), and security (j). We control for security-specific characteristics, credit rating and time-fixed effects.

Second, to test hypothesis 2, we use our *full sample* of 4,190 tranches. Hence, we include all tranches rated by Moody's, S&P, DBRS, and KBRA regardless of whether they received one or multiple credit ratings. To test how CRAs' rating standards vary with higher or lower market share of its competitors (hypothesis

2), we follow Blume et al. (1998) and Alp (2013) and apply the following ordered logit model:

$$R_{it} = \begin{cases} 21 \; if Z_{it} \in [\mu_{21}, \; \infty) \\ 20 \; if Z_{it} \in [\mu_{20}, \; \mu_{20}) \\ \vdots \\ 2 \; if Z_{it} \in [\mu_{1}, \; \mu_{2}) \\ 1 \; if Z_{it} \in [-\infty, \; \mu_{1}) \end{cases} \tag{4.2}$$

$$Z_{it} = \alpha_t + \beta' X_{it} + \epsilon_{it} \tag{4.3}$$

$$E[\in_{it} | X_{it}] = 0, \tag{4.4}$$

where R_{it} denotes the credit rating of security *i* in issuance year *t*. α_t is the intercept for year *t*, β is the vector of slope coefficients, and Z_{it} is a latent variable that relates to R_{it} in the ranges between different partition points μ_i. R_{it} ranges from 1 to maximum 20. The matrix X_{it} denotes columns with explanatory variables including *Tranche Count, Subordination Level, Number of Ratings, Log Tranche Value, Log Transaction Value, Top Ten Issuer,* and *Coupon*. The variable definitions are described in Section 4.3. The coefficient values in ordered logit models are reported in units of latent variables and consequently not economically relevant as the year indicator coefficient a_t is not in the same unit as Z_{it}. We follow Alp (2013) and Liu and Wang (2019) to convert a_t into the unit of rating notch, that is, the average distance between the partition points. The average rating notch length is calculated for each CRA separately.[48]

Third, in our final set of tests, we compare all tranches that received at least a rating of a large and a small CRA to test whether issuer size is related to better

[48] For example, Moody's provide credit ratings in our sample that range from 1(AAA) to 19(Caa3). The average rating notch length for Moody's will be calculated as (µ19 - µ1)/18= 0.63.

ratings by small CRAs. This leaves us with 2,155 tranches, representing our final subsample to test our third hypothesis. We use a logit model to investigate the impact of issuer's size on the rating quality of small CRAs (hypothesis 3):

$$\textit{Higher by Small}_{jt} = \alpha_0 + \alpha_1 \textit{ Issuer Size}_{ijt} + \textit{Tranche, Issuer and Market Controls}_{ijt} + \epsilon_{ijt} \tag{4.5}$$

All variables in Equations (4.1) and (4.5) are defined in Section 4.3.

4.5 Results

In this section, we examine the impact of competition in the market for credit ratings on rating differences and standards. We start by analyzing the impact of higher or lower market share on the rating difference between small and large CRAs in Section 4.5.1. We analyze the impact of competition in the CRA market on CRAs' rating quality. In Section 4.5.2, we examine if competition in the credit rating market has an impact on the rating standards of CRAs. We expect that CRAs react to more competition by adjusting their rating standards as a competitive strategy. Moreover, it is expected that the power of issuers plays an important role in competition among CRAs. To examine this issue, we look at the size of issuers in Section 4.5.3, expecting that CRAs are more likely to provide better ratings for tranches issued by larger issuers.

Table 4.4 provides the regression results for Equation (4.1), the rating difference between small and large CRAs is the dependent variable and the market shares of large CRAs the key independent variable (H1A). In Table 4.5 we repeat the analysis of Table 4.4 but replace the key independent variables with the market shares of small CRAs (H1B). Table 4.6 presents the results of Equations (4.2), (4.3), and (4.4), where we regress the credit rating of a small CRA on the market share of large CRAs (H2A). In Table 4.7 we replicate the regressions of Table 4.6

but use the credit rating of large CRAs as dependent variables (H2B). We report the results of Equation (4.5) in Table 4.8, the rating differences between small and large CRAs is the dependent variable and the size of issuers is the primary independent variable (H3).

4.5.1 **Competition and rating differences**

The results of the ordered logit regressions (Equation 4.1) with the rating differences between large and small CRAs as dependent variables are shown in Table 4.4. Panel A of Table 4.4 presents odds ratios of regressions for tranches rated by DBRS. We only use tranches that received a rating by both a large and a small CRA as we are interested in the rating differences between large and small CRAs. We use two subsamples for tranches rated by DBRS: one for tranches rated by DBRS and Moody's (columns 1 to 4) and one for tranches rated by DBRS and S&P (columns 5 to 8). We perform a similar analysis for KBRA in Panel B of Table 4.4, where we also split our sample into two subsamples: one for tranches rated by KBRA and Moody's (columns 1 to 4) and one for tranches rated by KBRA and S&P (columns 5 to 8). In both panels of Table 4.4 we use all our measures of market share for larger CRAs, as specified in Section 4.3.2, as independent variables.[49]

First, we study the tranches rated by both DBRS and Moody's in columns (1) to (4) of Panel A. In column (1) of Panel A we find that the odds ratio of *MS Moody's by Balance* is negative and statistically significant (with odds of −8.22), indicating that a one standard deviation increase in market share by Moody's increases the odds of experiencing a worse rating by DBRS, compared to Moody's, for the same tranche. With a worse rating we mean a rating that is less optimistic, so further

[49] In an unreported test we perform the same regression as in Table 4.4, but we split the sample between tranches issued in the US and the EU market. We do so as the market shares of CRAs differ across markets (e.g., see Figure 4.1 and Table 4.3). We find similar results as reported in Table 4.4, with slightly higher significant levels for tranches issued in the US market. For KBRA, the number of observations in the EU market is too low to perform statistical analysis.

away from AAA, compared to the other rating assigned for the same tranche. We find similar results when we use our market share measure by frequency, albeit at the 5% significance level (column 2) and consistent highly significant results when we use our combined market share measure for large CRAs (columns 3 and 4).

Next, we study the tranches rated by both DBRS and S&P in columns (5) to (8) of Panel A. In column (5) we find that the odds ratio of *MS S&P by Balance* is negative, but only significant at the 10% significance level. We do find negative significant results, at the 5% level, for our *MS S&P by Frequency* measure of market share in column (6) of Panel A. We find that a one standard deviation increase in *MS S&P by Frequency* increases the odds of experiencing a worse rating by DBRS than by S&P for the same tranche. Consistent results are found for our combined market share measure for large CRAs, *MS Large CRAs by Balance*, with the odds of −3.89, statistically significant at the 5% level (z-statistic of −1.97), column (7).

In sum, the results of Panel A of Table 4.4 suggest that the higher market share of a large CRA results, on average, in a higher likelihood of a worse rating by DBRS than the rating assigned by Moody's for the same tranche. So, DBRS is giving worse ratings, on average, than Moody's when Moody's is increasing its market share.

We find opposite results for tranches rated by KBRA and Moody's in columns (1) to (4) of Panel B of Table 4.4. In column (1) of Panel B, we find that the odds ratio of *MS Moody's by Balance* is positive, but only statistically significant at the 5% level (z-statistic of 2.22). This indicates that a one standard deviation increase in *MS Moody's by Balance* increases the odds of experiencing a better rating by KBRA than from Moody's, for the same tranche. We find consistent significant results (again at the 5% significance level) for the market share measures *MS Moody's by Tranche* in column (2), and for our combined market share measure for large CRAs in columns (3) and (4). However, if we move to the tranches rated by KBRA and S&P in column (4) to (8) in Panel B, we find no significant results at all for our market share measures.

Overall, the results of Table 4.4 show that DBRS and KBRA react differently to higher or lower market shares from its larger peers. Specifically, we find that a higher market share of the large CRAs results in a lower likelihood of a better (closer to AAA) rating from DBRS for the same tranche. So, DBRS is not providing the better credit rating, Moody's or S&P are. KBRA, however, does provide the better rating compared to that of Moody's with an increasing market share. This means that our first hypothesis (H1A), that with a higher market presence of a large CRA, small CRAs tend to report better ratings than large CRA, can only be supported for KBRA, not for DBRS.

In Table 4.5, we repeat our analysis of Table 4.4, but replace our dependent variables (the market shares of the larger CRAs) by the market shares of the smaller CRAs. We do so as we are also interested in the impact that the smaller CRAs have on the large CRAs, especially since the market share of small CRAs is increasing remarkably in the RMBS market over the last years. Panel A of Table 4.5 presents the odds ratios of regressions for tranches rated by Moody's. We again use only tranches that received a rating of both a large and a small CRA, so we construct the following subsamples: one for tranches rated by Moody's and DBRS (columns 1 to 4) and one for tranches rated by Moody's and KBRA (columns 5 to 8). We perform a similar analysis for S&P in Panel B of Table 4.5, where we also split our sample in two subsamples: one for tranches rated by S&P and DBRS (columns 1 to 4) and one for tranches rated by S&P and KBRA (columns 5 to 8). In both panels of Table 4.5, we use all our measures of market share for smaller CRAs, as specified in Section 4.3.2, as independent variables.

Firstly, we analyze the tranches rated by both Moody's and DBRS in columns (1) to (4) of Panel A. We find no significant effect for our first market share measure of DBRS, *MS DBRS by Balance*, in column (1) of Panel A. However, for our other market share measure of DBRS in column (2), we find highly significant results; the odds ratio of *MS DBRS by Tranche* is positive and statistically significant (z-stat = 3.41), indicating that a one standard deviation increase in market share by DBRS increases the odds of experiencing a better rating by DBRS, compared to Moody's, for the same tranche. We find consistent results when we use our combined market share measure for large CRAs (columns 3 and 4). This indicates that Moody's does *not* have the tendency, on average, to provide a better rating (one closer to AAA) than DBRS when competition in the CRA market intensifies by DBRS. When we move to our sample of tranches rated by Moody's and KBRA, in columns (5) to (8) of Panel A, we observe that the sign of the coefficients changes from positive to negative. We find that the odds ratios of our market share measures for KBRA, *MS KBRA by Balance* (column 5) and *MS KBRA by Tranche* (column 6), are negative but only significant at the 5% significance level. For example, a one standard deviation increase in *MS KBRA by Tranche* decreases the odds, with −306.1 (z-stat = −2.22), of experiencing a better rating by KBRA than by Moody's for the same tranche. We find consistent results for our combined market share measure *MS Small CRAs by Balance* and *MS Small CRAs by Tranche* in columns (7) and (8).

Secondly, we study the tranches rated by S&P in Panel B of Table 4.5. For tranches rated by S&P and DBRS in columns (1) to (4) in Panel B, we find only slightly positive significant results (at the 5% level) for one of our combined market share measures of small CRAs, *MS Small CRAs by Balance* (column 3). We find no significant results for our market share measures of DBRS in columns (1) and (2). Besides, we find no significant results at all for tranches rated by S&P and KBRA in columns (5) to (8) of Panel B.

The results of Table 4.5 suggest that, with higher market share of DBRS, Moody's is more likely to assign a worse (further away from AAA) rating compared to DBRS for the same tranche. This suggests that Moody's does not assign better ratings to retain or gain market shares when competition of DBRS intensifies. We find no significant results that S&P assigns either worse or better ratings compared to its smaller peers when the market share of small CRAs is higher. Hence, we cannot support our second hypothesis (H1B) in which we posit that with a higher market presence of a small CRA, large CRAs tend to report better ratings than small CRAs. We actually find that the opposite effect is more likely for tranches rated by Moody's and DBRS; on average, Moody's ratings are worse when the market share of DBRS is higher.

Table 4.4: Ordered logit regressions of market share of large CRAs on rating differences.

This table reports ordered logit regressions of the market share of large CRAs on rating differences, controlled for deal-level characteristics and market conditions. We use the sample of RMBS securities issued in the first quarter of 2017 up to the third quarter of 2020. The sample is based on securities that received a rating from at least one large CRA (Moody's and/or S&P) and at least one small CRA (DBRS and/or KBRA) as reported on Bloomberg. The dependent variables 'Rating Differences Moody's – DBRS' stands for the numerical value of Moody's rating minus the numerical value of DBRS' rating. 'Rating Differences S&P – DBRS' stands for the numerical value of S&P's rating minus the numerical value of DBRS' rating. 'Rating Differences Moody's – KBRA' stands for the numerical value of Moody's rating minus the numerical value of KBRA's rating. 'Rating differences S&P – KBRA' stands for the numerical value of S&P's rating minus the numerical value of KBRA's rating. The independent variables 'MS Moody's by Frequency' and 'MS S&P by Frequency' represent the percentage of the number of tranches rated by Moody's and S&P in a given year and market. 'MS Moody's by Balance' and 'MS S&P by Balance' represent the percentage of total tranche value rated by Moody's and S&P in a given year and market. 'Large CRAs by Balance' stands for the combined market share, measured in terms of balance size, of Moody's, S&P, and Fitch in a given year and market. 'Large CRAs by Frequency' stands for the combined market share, measured in terms of balance size, of Moody's, S&P, and Fitch in a given year and market. 'Year' represent the year of issuance, which equals a dummy of 1 that corresponds to the year the RMBS was issued, zero otherwise. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Geography of Collateral' represent the geographic location of the (majority of the) underlying collateral for each tranche. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for tranches rated by DBRS and Moody's or S&P. Panel B presents results for tranches rated by KBRA and Moody's or S&P.

Panel A: DBRS sample

	Rating Differences Moody's – DBRS				*Rating Differences S&P – DBRS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS Moody's by Balance	-8.22***							
	(-3.53)							
MS Moody's by Tranche		-10.04**						
		(-2.28)						
MS Large CRAs by Balance			-6.50***				-3.89**	
			(-4.69)				(-1.97)	
MS Large CRA by Tranche				-8.85***				-3.93*
				(-5.75)				(-1.68)
MS S&P by Balance					-9.38*			
					(-1.90)			
MS S&P by Tranche						-9.29**		
						(-2.14)		

Table 4.4: Continued

Year	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y	Y	Y	Y	Y
Geography of Collateral	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Moody's/ DBRS	Moody's/ DBRS	Moody's/ DBRS	Moody's/ DBRS	SP/ DBRS	SP/ DBRS	SP/ DBRS	SP/ DBRS
Observations	721	721	721	721	502	502	502	502
Pseudo R2	0.179	0.175	0.183	0.189	0.348	0.349	0.349	0.348

Panel B: KBRA sample

	Rating Differences Moody's – KBRA				*Rating Differences S&P – KBRA*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS Moody's by Balance	40.78**							
	(2.22)							
MS Moody's by Tranche		38.30**						
		(2.22)						
MS Large CRAs by Balance			153.6**				-50.92	
			(2.22)				(-0.78)	
MS Large CRA by Tranche				164.1**				-54.42
				(2.22)				(-0.78)
MS S&P by Balance					61.87			
					(0.78)			
MS S&P by Tranche						58.23		
						(0.78)		
Year	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y	Y	Y	Y	Y
Geography of Collateral	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Moody's/ KBRA	Moody's/ KBRA	Moody's/ KBRA	Moody's/ KBRA	SP/ KBRA	SP/ KBRA	SP/ KBRA	SP/ KBRA
Observations	582	582	582	582	230	230	230	230
Pseudo R2	0.297	0.297	0.297	0.297	0.481	0.481	0.481	0.481

Table 4.5: Ordered logit regressions of market share of small CRAs on rating differences.

This table reports ordered logit regressions of the market share of small CRAs on rating differences, controlled for deal-level characteristics and market conditions. We use the sample of RMBS securities issued in the first quarter of 2017 up to the third quarter of 2020. The sample is based on securities that received a rating from at least one large CRA (Moody's and/or S&P) and at least one small CRA (DBRS and/or KBRA) as reported on Bloomberg. The dependent variables 'Rating Differences Moody's – DBRS' stands for the numerical value of Moody's rating minus the numerical value of DBRS' rating. 'Rating Differences S&P – DBRS' stands for the numerical value of S&P's rating minus the numerical value of DBRS' rating. 'Rating Differences Moody's – KBRA' stands for the numerical value of Moody's rating minus the numerical value of KBRA's rating. 'Rating differences S& – KBRA' stands for the numerical value of S&P's rating minus the numerical value of KBRA's rating. The independent variables MS DBRS by Frequency' and 'MS KBRA by Frequency' represent the percentage of the number of tranches rated by DBRS and KBRA in a given year and market. 'MS DBRS by Balance' and 'MS KBRA by Balance' represent the percentage of total tranche value rated by DBRS and KBRA in a given year and market. 'Small CRAs by Balance' stands for the combined market share, measured in terms of balance size, of DBRS and KBRA in a given year and market. 'Small CRAs by Frequency' stands for the combined market share, measured in terms of balance size, of DBRS and KBRA in a given year and market. 'Year' represent the year of issuance, which equals a dummy of 1 that corresponds to the year the RMBS was issued, zero otherwise. 'Credit Rating' are a set of dummy variables to indicate the credit rating of a security at issuance, after we convert the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. 'Geography of Collateral' represent the geographic location of the (majority of the) underlying collateral for each tranche. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for tranches rated by Moody's and DBRS or KBRA. Panel B presents results for tranches rated by S&P and DBRS or KBRA.

Panel A: Moody's sample

	Rating Differences Moody's – DBRS				*Rating Differences Moody's – KBRA*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS DBRS by Balance	-5.01							
	(-1.11)							
MS DBRS by Tranche		23.65***						
		(3.41)						
MS Small CRAs by Balance			6.50***				-153.1**	
			(4.69)				(-2.22)	
MS Small CRA by Tranche				8.85***				-163.5**
				(5.76)				(-2.22)
MS KBRA by Balance					-72.14**			
					(-2.22)			

Table 4.5: Continued

MS KBRA by Tranche						-306.1**		
						(-2.22)		
Year	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y	Y	Y	Y	Y
Geography of Collateral	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Moody's/ DBRS	Moody's/ DBRS	Moody's/ DBRS	Moody's/ DBRS	Moody's/ KBRA	Moody's/ KBRA	Moody's/ KBRA	Moody's/ KBRA
Observations	721	721	719	719	582	582	582	582
Pseudo R2	0.173	0.178	0.183	0.189	0.297	0.297	0.297	0.297

Panel B: S&P sample

	Rating Differences S&P – DBRS				*Rating Differences S&P – KBRA*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS DBRS by Balance	11.71							
	(1.50)							
MS DBRS by Tranche		3.27						
		(0.34)						
MS Small CRAs by Balance			3.89**				50.76	
			(1.97)				(0.78)	
MS Small CRA by Tranche				3.92*				54.24
				(1.67)				(0.78)
MS KBRA by Balance					23.92			
					(0.78)			
MS KBRA by Tranche						101.5		
						(0.78)		
Year	Y	Y	Y	Y	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y	Y	Y	Y	Y
Geography of Collateral	Y	Y	Y	Y	Y	Y	Y	Y
Sample	SP/DBRS	SP/DBRS	SP/DBRS	SP/DBRS	SP/KBRA	SP/KBRA	SP/KBRA	SP/KBRA
Observations	502	502	502	502	230	230	230	230
Pseudo R2	0.347	0.346	0.349	0.348	0.481	0.481	0.481	0.481

4.5.2 **Competition and rating standards**

There are at least two caveats regarding the interpretation of the outcomes in Tables 4.4 and 4.5. First, the impact of competition could be overstated because the sample of tranches for which we use rating differences may not be representative of all rated tranches in the RMBS market. Second, the positive (negative) relation between market share of CRAs and rating differences could arise when the CRA applies tighter (looser) rating standards as it has higher (lower) market powers in the first place. Meaning, the relation could be due to worse (better) ratings from the large CRAs rather than better (worse) ratings from the small CRAs (Bae et al., 2019). To address the issue, we run ordered logit regressions to measure how CRA's rating standards vary with higher and lower market shares of its competitors (Equations 4.2 to 4.4). The results are presented in Tables 4.6 and 4.7. The ordered logit model has been extensively used in the literature to identify changes in rating standards (see e.g., Blume et al., 1998; Alp, 2013; Bae et al., 2019).

In Table 4.6, we use DBRS' and KBRA's rating as the dependent variable and the market share of large CRA (Moody's and S&P) as the key independent variables. In our regression model in Panel A, we use the sample of all tranches rated by DBRS (columns 1 to 4), irrespective of whether they are rated by another CRA. We also do this for KBRA (columns 5 to 8). To control for the determinants of credit ratings, we include the following variables: *Number of Ratings, Tranche Count, Subordination Level, Log Tranche Value, Log Transaction Value, Top Ten Issuer,* and *Coupon*. We also include year dummy variables and control for the country in which the collateral is located. All variables are explained in detail in Section 4.3. In Table 4.6, a statistically significant negative coefficient for our market share measures, *MS Moody's by Frequency* and *MS S&P by Frequency*, indicates that the small CRA loosen its rating standards with higher market share of the larger CRA. An insignificant coefficient suggests that the market share of a large CRA is unrelated to the small CRA's rating standards, and a significant positive coefficient indicates that the small CRA tightens its rating standards with a higher market share of the large CRA.[50]

We start by looking at the rating standards of DBRS in columns (1) to (4) of Panel A. Column (1) shows a negative significant coefficient for *MS Moody's by Frequency*, and this effect is also economically significant, as shown in column (2) which present the economic magnitude of the coefficient estimates.[51] This indicates that a one-standard deviation increase in Moody's market share corresponds to an upgrade of 0.94 notch in DBRS' ratings. Interestingly, we find no significant result for S&P's market share in column (3). This suggests that DBRS loosens its rating standards more when it faces more competition from Moody's, but not from S&P. We are also interested in the control variable *Number of Ratings* as it indicates whether DBRS adjust its rating standards to a greater extent when dealing with dual or triple rated tranches, compared to a single DBRS rating. In columns (1) and (2) we observe a negative coefficient for *Number of Ratings*, indicating that a one-standard deviation increase in the number of ratings corresponds to an upgrade of a 0.76 notch in DBRS' rating. We find similar results in columns (3) and (4). Hence, DBRS is more likely to provide better ratings when a tranche also received a rating from another CRA. Next, we move to the sample of all KBRA-rated tranches to analyze KBRA's rating standards, reported in columns (5) to (8) in Panel A. Interestingly, we find no significant results in columns (5) to (8), suggesting that the market share of large CRAs and *Number of Ratings* is unrelated to KBRA's rating standards.

[50] In other tests we have repeated the regression models in Tables 4.6 and 4.7 with our other market share measures: MS DBRS by Balance, MS KBRA by Balance, MS Small CRAs by Balance, and MS Small CRA by Tranche, and find similar results.

[51] The coefficient estimates in an ordered logit model show the units of the latent variable, making it rather difficult to understand the economic significance. Therefore, in line with Alp (2013), we estimate the average change in ratings that would results from a change in the relevant explanatory variable. The economic magnitude is calculated as follows: the coefficient of the explanatory variable, for example Tranche Count, is multiplied by its standard deviation and divided by the average rating notch length (measured in terms of latent variables). For a dummy variable, such as Top Ten Issuer, this means that the coefficient is only divided by the rating notch length.

In Panel B of Table 4.6 we perform a similar analysis as in Panel A of Table 4.6, but we reduce our sample to tranches that received a rating by a large and a small CRA. We do so as we are interested in whether small CRAs adjust their rating standards to a greater extent when the exact same tranche also received a rating from a specific larger competitor (Moody's or S&P). We split our sample in tranches rated by: Moody's and DBRS (columns 1 and 2), S&P and DBRS (columns 3 and 4), Moody's and KBRA (columns 5 and 6), and S&P and KBRA (columns 7 and 8).

We start by comparing the results for DBRS in Panel B (columns 1 to 4) with the results for DBRS in Panel A (columns 1 to 4). In Panel B, we observe results consistent with Panel A for DBRS; a negative and highly significant coefficient for *MS Moody's by Frequency* (column 1) and no significant results for the market share measure of S&P (*MS S&P by Frequency*). If we move to the subsamples of KBRA in columns (5) to (8) of Panel B, we observe negative odds ratios of −13.7 (z-stat = −4.35) for Moody's market share measure (*MS Moody's by Frequency*), statistically significant at the 1% level. The economic magnitude of the coefficient estimates indicates that a one standard deviation increase in market share by Moody's (*MS Moody's by Frequency*) corresponds to an upgrade of 1.06 in KBRA's rating (column 6), for tranches rated by both Moody's and KBRA. We also find a negative coefficient for S&P's market share measure (*MS S&P by Frequency*) in column 7, but only at the 5% significance level. Remarkably, KBRA tends to adjust (loosen) its rating standards when the tranche also received a rating of a larger CRA (Panel B) but does not adjust its standards when we consider all tranches rated by KBRA, including single and triple rated tranches (Panel A).

Overall, the results of Table 4.6 show that DBRS and KBRA tend to loosen their rating standards as a competitive strategy against Moody's, but not necessarily S&P. For DBRS, we find that it tends to loosen its rating standards when Moody's market share is higher, both when the tranche is and is not rated by Moody's as well. DBRS does not adjust its rating standards when the competition of

S&P intensifies (i.e., higher market shares of S&P). Apparently, DBRS is more sensitive to competition with Moody's and while it loosens its rating standards with heightened competition from Moody's (Table 4.6), it still does not provide a better rating on average for the same tranche (Table 4.4). While for KBRA, we find that it tends to loosen its rating standards when competition from Moody's intensifies, but only when the same tranche also received a Moody's rating. This finding is consistent with the results of Table 4.5, where we find that KBRA assigns better ratings on average when the tranche is also rated by Moody's. The findings of Table 4.6 suggest that H2A, in which we posit that with higher competitive pressure, small CRAs are more likely to loosen their rating standards, is supported, but only for higher competitive pressures of Moody's and not from S&P.

In Table 4.7 we repeat the regression models of Table 4.6, but we replace our dependent variables (the market share of large CRAs) with the market share of smaller CRAs, and we use Moody's and S&P's rating as the dependent variables. By doing so we can analyze the opposite effect to address whether large CRAs react upon the relative new competition of the smaller CRAs by adjusting their rating standards. In Panel A of Table 4.7 we use all tranches in our sample that received at least one rating from Moody's (columns 1 to 4) and similarly for S&P (columns 5 to 8). We find no significant results for the market share measures of DBRS (*MS DBRS by Frequency*) and KBRA (*MS KBRA by Frequency*) in the Moody's sample in columns (1) to (4). However, we do observe statistically significant negative coefficients for the *Number of Ratings*. The magnitude in column (2) indicates that a one-standard deviation increase in the number of ratings corresponds to an upgrade of 1.58 in Moody's rating. So, Moody's is more likely to adjust its rating standards when the tranche also received a rating from another CRA than for tranches that only received a rating from Moody's. We find similar results if we add KBRA's market share to the model in column (4).

If we move to the rating standards of S&P, in columns (5) to (8), we find statistically significant negative coefficients for our market share measures of DBRS (*MS DBRS by Frequency*) and KBRA (*MS KBRA by Frequency*), indicating that S&P tends to loosen its rating standards when the market share of the small CRAs is higher. Specifically, we find that a one-standard deviation increase in market share of DBRS (KBRA) corresponds to an upgrade of 1.88 (2.08) notch in S&P's rating. Furthermore, similar to Moody's, we also find that S&P tends to upgrade its credit rating when the tranche is rated by two or three CRAs. This result is indicated by the negative significant coefficient for *Number of Ratings* in both columns (5) and (8).

In Panel B of Table 4.7, we again limit our sample to tranches that received a rating from both a small and a large CRA. We split our sample in tranches rated by Moody's and DBRS (columns 1 and 2), Moody's and KBRA (columns 3 and 4), S&P and DBRS (columns 5 and 6), and S&P and KBRA (columns 7 and 8). We do so to analyze if large CRAs adjust their rating standards differently when the tranche also obtained a credit rating of a smaller CRAs. We find that Moody's does when a tranche also received a rating of KBRA. This result is provided in column (3) of Panel B, where we observe a positive significant coefficient for *MS KBRA by Frequency*, with odds of 56.34 (z-stat = 2.77). The economic magnitude of the coefficient estimate is presented in column (4). The magnitude indicates that a one-standard deviation increase in market share of KBRA corresponds to a downgrade of 8.57 notch in Moody's rating. We find no significant results for DBRS' market share measure, *MS DBRS by Frequency*. This means that Moody's is not likely to adjust its rating standards when market share from DBRS is higher. If we look at the rating standards of S&P in columns (5) to (8) in Panel B, we observe no highly significant results for our market share measures of small CRAs.

Overall, not only small CRAs, but also the large incumbents modify their rating standards when competition of their smaller peers is higher. Concretely, we find that Moody's is likely to tighten its rating standards when competition from KBRA intensifies, but only when the tranche is rated by both Moody's and KBRA. While S&P tends to loosen its rating standards when the competitive pressures of DBRS and KBRA is higher, this occurs only when the tranche is not rated by a small CRA. Rather, S&P loosened its standard when the tranche received a rating from: S&P only; S&P and Moody's or; S&P and Fitch. This suggests that S&P is less sensitive to higher or lower market share of its smaller competitors.

Table 4.6: Ordered logit regressions of market share of large CRAs on the credit rating of small CRAs.

This table reports ordered logit regressions of the market share of large CRAs on the credit rating of small CRAs, controlled for deal-level characteristics, issuer characteristics and market conditions. We use the full sample of RMBS securities issued in the first quarter of 2017 up to the third quarter of 2020. The sample is based on securities that received at least one rating from DBRS or KBRA as reported on Bloomberg. The dependent variable are the numerical values of a credit rating of the tranches at issuance, we use the numerical values of the credit rating of DBRS and KBRA as dependent variables. We have converted the ratings into a numerical value by setting 1 for AAA (AA+), 2 for AA (AA), 3 for AA (AA-), and so on. The key independent variables 'MS Moody's by Frequency' and 'MS S&P by Frequency' represent the percentage of the number of tranches rated by Moody's and S&P in a given year and market. All other independent variables are defined in Table 4.2. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for all (single, dual, and triple) tranches that received a rating by DBRS and KBRA; Panel B for dual rated tranches by large and small CRA only.

Panel A: Rating Standards of small CRAs – full samples

	DBRS sample only *(Dependent=DBRS rating)*				***KBRA sample only*** *(Dependent=DBRS rating)*			
	Coefficient (P-value)	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS Moody's by Frequency	-12.14***	-0.94			10.61	0.82		
	(-3.74)				(1.36)			
MS S&P by Frequency			1.11	0.12			-48.65	-5.39
			(0.31)				(-1.36)	
Number of Ratings	-1.13***	-0.76	-1.17***	-0.78	-0.62*	-0.42	-0.62*	-0.42
	(-5.94)		(-6.14)		(-1.91)		(-1.91)	
Tranche Count	-0.29***	-2.31	-0.29***	-2.27	-0.37***	-2.99	-0.37***	-2.99
	(-10.59)		(-10.43)		(-7.10)		(-7.10)	
Subordination Level	-0.21	-0.08	-0.22	-0.08	-0.16	-0.06	-0.16	-0.06
	(-1.17)		(-1.27)		(-0.70)		(-0.69)	
Log Tranche Value	-2.38***	-4.20	-2.36***	-4.16	-3.63***	-6.44	-3.63***	-6.44
	(-28.61)		(-28.53)		(-24.6)		(-24.6)	
Log Transaction Value	2.82***	2.98	2.80***	2.95	2.11***	2.25	2.11***	2.25
	(18.79)		(18.52)		(8.63)		(8.63)	
Top Ten Issuer	0.01	0.01	-0.04	-0.05	0.52	0.57	0.52	0.57

Table 4.6: Continued

Coupon	0.79***	1.45	0.79***	1.44	0.81***	1.50	0.81***	1.50
	(14.67)		(14.67)		(9.46)		(9.46)	
Year	Y		Y		Y		Y	
Geography of Collateral	Y		Y		Y		Y	
Sample	DBRS only		DBRS only		KBRA only		KBRA only	
Observations	2,010		2,010		1,661		1,661	
Pseudo R2	0.345		0.345		0.483		0.483	

Panel B: Rating Standards of small CRAs - split samples

	DBRS subsamples *(Dependent=DBRS rating)*				**KBRA subsamples** *(Dependent=KBRA rating)*			
	Coefficient (P-value)	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS Moody's by Frequency	-16.55***	-1.27			-13.7***	-1.06		
	(-3.75)				(-4.35)			
MS S&P by Frequency			-4.00	-0.44			-66.26**	-7.35
			(-0.77)				(-2.04)	
Tranche Count	-0.23***	-1.86	0.04	0.31	-0.35***	-2.85	-0.26***	-2.11
	(-8.86)		(1.16)		(-6.52)		(-5.93)	
Subordination Level	-0.32	-0.12	-0.15	-0.06	-0.07	-0.03	0.23	0.09
	(-1.31)		(-0.48)		(-0.23)		(0.52)	
Log Tranche Value	-1.99***	-3.50	-1.79***	-3.16	-3.43***	-6.08	-3.04***	-5.39
	(-18.62)		(-13.21)		(-16.02)		(-9.62)	
Log Transaction Value	1.82***	1.93	2.06***	2.17	2.86***	3.04	3.51***	3.73
	(12.25)		(13.77)		(7.11)		(11.44)	
Top Ten Issuer	0.87***	0.96	-0.08	-0.09	0.93**	1.03	-0.76*	-0.84
	(4.15)		(-0.38)		(2.52)		(-1.87)	
Coupon	0.65***	1.19	1.23***	2.25	0.63***	1.17	0.80***	1.48
	(6.35)		(12.05)		(3.97)		(4.39)	
Year	Y		Y		Y		Y	
Geography of Collateral	Y		Y		Y		Y	
Sample	Moody's/DBRS		S&P/DBRS		Moody's/KBRA		S&P/KBRA	
Observations	719		502		582		230	
Pseudo R2	0.287		0.29		0.435		0.397	

Table 4.7: Ordered logit regressions of market share of small CRAs on the credit rating of large CRAs.

This table reports ordered logit regressions of the market share of small CRAs on the credit rating of large CRAs, controlled for deal-level characteristics, issuer characteristics and market conditions. We use the full sample of RMBS securities issued in the first quarter of 2017 up to the third quarter of 2020. The sample is based on securities that received at least one rating from Moody's or S&P as reported on Bloomberg. The dependent variable are the numerical values of a credit rating of the tranches at issuance, we use the numerical values of the credit rating of Moody's and S&P as dependent variables. We have converted the ratings into a numerical value by setting 1 for Aaa (AAA), 2 for Aa1 (AA+), 3 for Aa2 (Aa), and so on. The key independent variables 'MS DBRS by Frequency' and 'MS KBRA by Frequency' represent the percentage of the number of tranches rated by DBRS and KBRA in a given year and market. All other independent variables are defined in Table 4.2. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents results for all (single, dual, and triple) tranches that received a rating by DBRS and KBRA; Panel B for dual rated tranches by large and small CRA only.

Panel A: Rating Standards of Large CRAs

	Moody's sample only *(Dependent=Moody's rating)*				***S&P sample only*** *(Dependent=S&P rating)*			
	Coefficient (P-value)	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS DBRS by Frequency	-2.51	-246.71			-28.93***	-1.88		
	(-0.56)				(-4.07)			
MS KBRA by Frequency			-2.01	-0.31			-20.65***	-2.08
			(-0.29)				(-3.00)	
Number of Ratings	-1.62***	-1.58	-1.64***	-1.59	-2.66***	-1.72	-2.60***	-1.68
	(-6.79)		(-6.93)		(-10.18)		(-9.92)	
Tranche Count	-0.16***	-1.83	-0.16***	-1.79	0.20***	1.54	0.19***	1.46
	(-5.82)		(-5.83)		(3.28)		(3.08)	
Subordination Level	0.02	0.01	0.02	0.01	0.05	0.02	0.05	0.02
	(0.14)		(0.12)		(0.20)		(0.21)	
Log Tranche Value	-2.20***	-5.61	-2.19***	-5.60	-2.02***	-3.42	-2.01***	-3.41
	(-28.10)		(-28.11)		(-18.15)		(-18.15)	
Log Transaction Value	1.87***	2.87	1.88***	2.87	1.64***	1.67	1.93***	1.96
	(13.14)		(13.17)		(6.96)		(8.64)	

Table 4.7: Continued

Top Ten Issuer	0.64*	1.03	0.63*	1.01	-1.97***	-2.08	-2.15***	-2.28
	(1.82)		(1.80)		(-3.11)		(-3.44)	
Coupon	0.43***	1.15	0.43***	1.16	1.15***	2.02	1.14***	2.01
	(7.01)		(7.10)		(14.54)		(14.53)	
Year	Y		Y		Y		Y	
Geography of Collateral	Y		Y		Y		Y	
Observations	1,583		1,583		1,018		1,018	
Pseudo R2	0.293		0.293		0.356		0.354	

Panel B: Rating Standards of Large CRAs - Split samples

	Moody's subsamples *(Dependent=Moody's rating)*				***S&P subsamples*** *(Dependent=S&P rating)*			
	Coefficient (P-value)	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*	*Coefficient (P-value)*	*Economic magnitude*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MS DBRS by Frequency	-5.37	-0.53			5.20	0.34		
	(-0.90)				(0.88)			
MS KBRA by Frequency			56.34***	8.57			-110.3**	-11.12
			(2.77)				(-2.12)	
Tranche Count	-0.20***	-2.36	-0.16***	-1.90	-0.07**	-0.54	-0.127***	-0.97
	(-8.82)		(-3.87)		(-2.13)		(-3.46)	
Subordination Level	-0.04	-0.02	-0.39	-0.21	-0.00	-0.00	0.68*	0.24
	(-0.19)		(-1.50)		(-0.00)		(1.65)	
Log Tranche Value	-1.81***	-4.61	-2.61***	-6.66	-1.73***	-2.93	-2.21***	-3.75
	(-19.92)		(-18.00)		(-13.80)		(-10.19)	
Log Transaction Value	1.79***	2.75	1.85***	2.84	2.16***	2.20	2.70***	2.75
	(12.59)		(5.89)		(14.49)		(11.85)	
Top Ten Issuer	0.73***	1.17	0.55*	0.87	-0.29	-0.30	-0.46	-0.49
	(3.96)		(1.82)		(-1.34)		(-1.27)	
Coupon	0.53***	1.42	0.43***	1.16	0.97***	1.71	0.51***	0.91
	(5.88)		(4.01)		(10.56)		(3.57)	
Year	Y		Y		Y		Y	
Geography of Collateral	Y		Y		Y		Y	
Sample	Moody's/DBRS		Moody's/KBRA		S&P/DBRS		S&P/KBRA	
Observations	719		582		502		230	
Pseudo R2	0.242		0.34		0.266		0.313	

Table 4.8: Logit regessions of the of issuer size on rating difference small vs. large CRAs.

This table reports logit regressions of the issuer size on the rating differences, controlled for deal-level characteristics, issuer characteristics and market conditions. We use the full sample of RMBS securities issued in the first quarter of 2017 up to the third quarter of 2020. The sample is based on securities that received a rating from at least one large CRA (Moody's and/or S&P) and at least one small CRA (DBRS and/or KBRA) as reported on Bloomberg. The dependent variable is the dichotomous variable 'Rating Differences' that equals 1 if, at issuance, a security received a better rating by a small CRA and zero if the rating at issue is worse by a small CRA. 'Issuer Size by Balance' is a dummy that equals 1 if the issuer is among the top 10% of issuers in the global RMBS market measured by size, and zero otherwise. 'Issuer Size by Frequency' is a dummy that equals 1 if the issuer is among the top 10% of issuers in the global RMBS market measured by tranche number, and zero otherwise. All other independent variables are defined in Table 4.5. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively. Panel A presents the tranches rated by DBRS or KBRA and a larger peer (Moody's/ S&P); Panel B divides the sample between tranches rated by only DBRS and a larger peer and tranches rated by KBRA and a larger peer.

Panel A: Full Sample (Dependent = Higher by Small)

	Issuer size measured by frequency		*Issuer size measured by balance size*	
	(1)	(2)	(3)	(4)
Issuer Size by Frequency	1.35***	0.51***		
	(11.56)	(3.44)		
Issuer Size by Balance			0.85***	0.34***
			(8.18)	(2.66)
Tranche Count		0.08***		0.09***
		(5.71)		(6.89)
Subordination level		0.62***		0.62***
		(3.92)		(3.96)
Log Tranche Value		-0.26***		-0.27***
		(-4.07)		(-4.20)
Log Transaction Value		0.39***		0.40***
		(4.63)		(4.80)
Coupon		-0.03		-0.04
		(-0.74)		(-0.77)
Year	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y
Observations	2,155	2,155	2,155	2,155
Pseudo R2	0.171	0.234	0.142	0.232

Panel B: Sample split (Dependent = Higher by Small)

	Tranches rated by DBRS		*Tranches rated by KBRA*	
	(1)	(2)	(3)	(4)
Issuer Size by Frequency	0.45**		0.77***	
	(2.50)		(2.61)	
Issuer Size by Balance		0.13		0.63***
		(0.86)		(2.69)
Tranche Count	0.001	0.02	0.08***	0.10***
	(0.06)	(0.68)	(2.82)	(3.60)
Subordination level	0.66***	0.63***	-0.01	0.02
	(3.12)	(2.99)	(-0.02)	(0.05)
Log Tranche Value	-0.40***	-0.41***	-0.35***	-0.33***
	(-4.72)	(-4.91)	(-2.97)	(-2.88)
Log Transaction Value	0.46***	0.51***	0.64***	0.61***
	(4.29)	(4.83)	(3.56)	(3.39)
Coupon	-0.05	-0.03	-0.01	-0.04
	(-0.79)	(-0.44)	(-0.07)	(-0.37)
Year	Y	Y	Y	Y
Credit Rating	Y	Y	Y	Y
Observations	1,223	1,223	812	812
Pseudo R2	0.156	0.153	0.390	0.390

4.5.3 **Competition and issuers' power**

The issuer-pays revenue model allows issuers to request credit ratings from several CRAs and only select the better ones. To increase the change of being selected by issuers, CRAs might provide more attractive ratings than their peers. This incentive may become greater when the credit rating is requested by a powerful, large issuer, who is potentially able to provide more future revenue for the CRA. So, competition among CRAs is found to be influenced by the power of issuers (e.g., see He et al., 2012). In this section, we test whether on average small CRAs provide better ratings in general and for the same tranche, than their larger competitors (Equation 4.5). Issuer size is our independent variable, used in two ways: whether they are large or small issuers measured by value of their market share (*Issuer Size by Balance*), and whether or not they are frequent issuers measured by the number of tranches they placed in the market (*Issuer Size by Frequency*). Our dependent variable is a dummy variable that equals one if the credit rating assigned by a small CRAs is better than the large CRA, and zero if the credit rating is equal or better by large CRAs.

The results are presented in Table 4.8. In Panel A we use all tranches that received a rating of DBRS or KBRA and a larger peer, and in Panel B we split our sample between DBRS and KBRA to test whether this effect is the same for both CRAs. In columns (1) and (3) of Panel A, we show that the odds ratio of issuer size is positive and significant for both *Issuer Size by Frequency* with an odd ratio of 1.35 (z-stat = 11.56) and *Issuer size by Balance* with odds of 0.85 (z-stat = 8.18). This suggests that large issuers increase the odds of experiencing a better rating by the smaller CRA. We observe similar results if we include our explanatory variables in the regression model in column (2) and (4). This finding suggests that large (or more powerful) issuers tend to influence credit ratings of small CRAs; the smaller CRA is more likely to provide better ratings, probably to increase its selection opportunity.

We now shift our attention to each of the small CRAs (DBRS and KBRA) separately in Panel B of Table 4.8 to assess whether this effect is the same for both DBRS and KBRA. We study the tranches that are rated by DBRS and a larger peer (columns 1-2) and tranches rated by KBRA and a larger peer (columns 3-4). Remarkably, both our issuer size measures are not highly significant for DBRS (columns 1-2). While for KBRA we observe highly significant results for *Issuer Size by Balance*; we find that large issuers (in terms of balance size) increase the odds of experiencing a better rating by KBRA by 63%, which is significant at the 1% level (z-stat = 2.69), column (4). The coefficient of the other issuer size measure, *Issuer Size by Frequency*, is also positive, with odds of 0.77, and highly significant at the 1% level, column (3).

To summarize, we find that small CRAs are more likely to provide a better rating than large CRAs, on average, when the tranche is issued by a more powerful issuer. Especially for KBRA, we see that issuers' power increases the likelihood of providing better credit ratings. It may well be that KBRA provide better credit ratings when dealing with more powerful issuers, to increase the chance of future revenue and, eventually, a higher market share. This means that we can support Hypothesis 3 in which we posit that large issuers tend to receive better ratings from small CRAs, compared to their larger peers.

4.6 Conclusion

The impact of competition in the structured finance market on rating quality has received substantial attention by academics and regulators in the last decade. Regulators have attempted to stimulate new entrants into the CRA industry. The question remains whether these rules and regulations have a positive effect on the quality of ratings. We analyze 4,190 RMBS tranches that were originated and sold from the first quarter of 2017 and the third quarter of 2020 to study the impact of competition on rating quality.

We provide evidence that competition between large (Moody's and S&P) and small (DBRS and KBRA) CRAs creates rating quality inconsistencies in the RMBS market. We find that especially Moody's and DBRS are sensitive to market share movements of one another; ratings become worse (on average, for the same tranche) when competition of Moody's or DBRS intensifies. Surprisingly, we find that KBRA shows the opposite effect when confronted with Moody's. KBRA provides better ratings on average when competition with Moody's intensifies. Furthermore, our results show that small CRAs tend to loosen their rating standards when the competitive pressure of their larger peers is higher, especially in the case of Moody's. While S&P seems to be less sensitive to market share movements of small CRAs, it does apply tighter rating standards for tranches that did not receive an additional rating of a small CRA.

Our results also show that small CRAs are sensitive to the power of issuers; they tend to provide better ratings when dealing with more powerful issuers, a finding that corresponds to the downside effects of the issuer-pays revenue model. This finding also suggests that the risk of reputational damages is not necessarily an effective deterring mechanism for small CRAs who must deal with competitors who have high global presence in the rating industry. In addition, we find that dual or triple rated tranches receive better ratings on average from CRAs, compared to single rated tranches. While at the same time, credit ratings of tranches that received a rating of both a large and a small CRA (dual rated tranches) are found to be influenced by competitive pressures of CRAs and power of issuers.

The CRA industry is an issuer-pay revenue model. Despite this revenue model (which depends on market share), investors using credit ratings to make investment decisions expect that the assigned ratings should not depend on the compensation received by a CRA. Hence, the credit rating should solely represent the underlying credit risk of an RMBS, regardless of the competition in the rating market. However, we find that CRAs adjust their credit rating based on competition. So apparently, CRAs consider not only underlying credit risk factors when assigning a credit rating to the tranches of an RMBS but also use ratings as a means to expand market share and revenue. Thus, our findings suggest that a regulatory environment that stimulates the use of multiple credit ratings and that encourages new CRAs to enter the market does not necessarily solve the problem of potential misleading credit ratings assigned by the prevailing market players.

References

Alp, A. (2013). Structural shifts in credit rating standards. *The Journal of Finance*, *68*(6), 2435–2470. https://doi.org/10.1111/jofi.12070

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*(5), 1011–1035. https://www.jstor.org/stable/43862285

Bae, K. H., Driss, H., & Roberts, G. S. (2019). Does competition affect ratings quality? Evidence from Canadian corporate bonds. *Journal of Corporate Finance, 58*, 605–623. https://doi.org/10.1016/j.jcorpfin.2019.07.009

Baghai, R. P., & Becker, B. (2020). Reputations and credit ratings: Evidence from commercial mortgage-backed securities. *Journal of Financial Economics, 135*(2), 425–444. https://doi.org/10.1016/j.jfineco.2019.06.001

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, *101*(3), 493–514. https://doi.org/10.1016/j.jfineco.2011.03.012

Blume, M. E., Lim, F., & Mackinlay, A. C. (1998). The declining credit quality of U.S. corporate debt: Myth or reality? *The Journal of Finance*, *53*(4), 1389–1413. https://www.jstor.org/stable/117406

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance, 67*(1), 85–111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Cafarelli, A. (2020). Creditworthiness risk over years: The evolution of credit rating standards. *Journal of Corporate Accounting & Finance*, *31*(4), 48–59. https://doi.org/10.1002/jcaf.22461

Camanho, N., Deb, P., & Liu, Z. (2020). Credit rating and competition. *American Finance Association 2011 Denver Meeting Paper*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1573035

Deku, S., Kara. A., & Marques-Ibanez, D. (2019). Trustee reputation in securitization: When does it matter? *Financial Markets, Institutions & Instruments, 28*(2), 61–84. https://doi.org/10.1111/fmii.12106

Dodd-Frank Wall Street Reform and Consumer Protection Act, Publ. L. No. 111–203, Section 941, Subsection 15G. (2010). https://www.govinfo.gov/link/plaw/111/public/203?link-type=pdf&.pdf

European Securities and Markets Authorities. (2020). *Report on CRA market share calculation.* https://www.esma.europa.eu/press-news/esma-news/esma-reports-annual-market-share-credit-rating-agencies-0

Flynn, S., & Ghent, A. (2018). Competition and credit ratings after the fall. *Management Science, 64*(4), 1477–1973. https://doi.org/10.1287/mnsc.2016.2604

Goldstein, I., & Huang, C. (2020). Credit rating inflation and firms' investments. *The Journal of Finance, 75*(6), 2929–2972. https://doi.org/10.1111/jofi.12961

Griffin, J. M., Nickerson, J., & Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *Review of Financial Studies*, *26*(9), 2270–2310. https://doi.org/10.1093/rfs/hht036

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. *The Journal of Finance*, *67*(6), 2097–2137. https://doi.org/10.1111/j.1540-6261.2012.01782.x

He, J. J., Qian, J. Q. J., & Strahan, P. E. (2015). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067

Höner, J. (2002). Reputation and competition. *American Economic Review*, *92*(3), 644–663. https://doi.org/10.1257/00028280260136444

Jewell, J., & Livingston, M. B. (2000). The impact of a third credit rating on the pricing of bonds. *The Journal of Fixed Income*, *10*(3), 69–85. https://doi.org/10.3905/jfi.2000.319275

Liu, S., & Wang, H. (2018). *What affects credit ratings in China? Evidence from the upgrades in the banking sector* [Unpublished paper]. Tsinghua University - School of Economics & Management. https://doi.org/10.2139/ssrn.3222997

Manso, G. (2013). Feedback effects of credit ratings. *Journal of Financial Economics*, *109*(2), 535–548. https://doi.org/10.1016/j.jfineco.2013.03.007

Morkoetter, S., Stebler, R., & Westerfeld, S. (2017). Competition in the credit rating industry: Benefits for investors and issuers. *Journal of Banking & Finance*, *75*, 235–257. https://doi.org/10.1016/j.jbankfin.2016.09.001

Rabanal, J. P., & Rud, O. A. (2017). Does competition affect truth telling? An experiment with rating agencies. *Review of Finance*, *22*(4), 1581–1604. https://doi.org/10.1093/rof/rfx012

Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013, amending Regulation (EC) No 1060/2009 on credit rating agencies, Article 8c. (2013). http://data.europa.eu/eli/reg/2013/462/oj

Regulation (EU) No 2017/2402 of the European Parliament and of the Council of 12 December 2017 laying down a general framework for securitisation and creating a specific framework for simple, transparent and standardised securitisation. (2017). http://data.europa.eu/eli/reg/2017/2402/oj

Securities and Exchange Commission. (2020). *Annual report on nationally recognized statistical rating organizations.* https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf

Skreta, V., & Veldkamp, L. (2009). Rating shopping and asset complexity: A theory of rating inflation. *Journal of Monetary Economics, 56*(5), 678–695. https://doi.org/10.1016/j.jmoneco.2009.04.006 ,

White, L. J. (2010). Markets: The credit rating agencies. *Journal of Economic Perspectives*, *24*(2), 211–226. https://doi.org/10.1257/jep.24.2.211

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: Rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Chapter 5

The Impact of Creditor Protection in US States on the RMBS market

Vivian M. van Breemen
Frank J. Fabozzi
Mike Nawas
Dennis Vink

Acknowledgement: *We thank Diana Bonfim (Banco de Portugal) and Dennis Reinhardt (Bank of England) for the invitation to participate in the 2022 Annual Conference of ESCB Research Cluster 3. We also thank the European Central Bank (ECB) for the invitation to participate in the ECB research seminar.*

Abstract

More than a dozen years after the Dodd-Frank Act has been introduced, we investigate whether credit ratings differ for the US residential mortgage-backed securities (RMBS) market given the different levels of creditor protection across the US states. Our paper provides three results. First, for the period 2017-2020, we provide evidence that there is inconsistency between CRAs: only for DBRS and Moody's we observe that their credit ratings differ for securitization tranches with different creditor protection level per state. Second, in states with higher creditor protection, the relatively new CRAs (DBRS and KBRA combined) are more likely to provide more optimistic ratings than CRAs historically present in the rating market (Moody's, S&P, and Fitch). Third, issuers appear to issue larger deals in US states that are more creditor friendly.

Keywords: creditor friendliness, credit rating agencies, issuers.

JEL classifications: G21, G24, G28, K25.

5.1 Introduction

The US capital markets attract investors globally, in part due to the effectiveness of the US market regulation developed to ensure the protection of investors and transparency of information (SEC, 2019). However, the Great Recession revealed that credit rating agencies (CRAs) assigned inflated credit ratings for tranches of private-label residential mortgage-backed securities (RMBS), resulting in the mispricing of these tranches (see, e.g., Griffin et al., 2013; He et al., 2016; Zhou et al., 2017; Flynn and Ghent, 2018). Many investors appeared not to be aware of the underlying risks in the pool of mortgages transactions (SEC, 2014). Investors who brought legal action parties in the securitization process to recover the large losses, realized as a result of the subprime mortgage crisis, that they were too late[52] when they tried to appeal to securities laws and had to eventually bear huge losses.[53]

The mass defaults on the underlying collateral starting in the summer of 2007 attributable to overoptimistic credit ratings for private-label RMBS issued in prior years[54], caused policymakers to pass the Dodd-Frank Act[55] aimed at improving the reliability of credit ratings. The Dodd-Frank established the SEC Office of Credit Rating, which stimulated the entry of two new CRAs (Dominion Bond Rating Service Morningstar (DBRS) and Kroll Bond Rating Agency (KBRA)) into the RMBS rating market to compete with Standard & Poor's Global Ratings (S&P), Fitch Ratings (Fitch), and Moody's Investors Service (Moody's).

In the United States, state laws offer lenders different levels of creditor protection.

[52] Investors were not able to redeem their losses on securitization transactions as federal securities laws only allowed investors to commence a lawsuit within a certain (short) time period, while the majority of investors discovered the nature of their claims only when this time period was already expired (Adelson, 2020).
[53] Estimated at $1 trillion losses from 2007 through 2016 (Adelson, 2020).
[54] One might argue that these losses were also attribute to the lack of understanding of these structured products and purchase them naively based solely on their yields.
[55] Dodd-Frank Act, 2010, Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Section 941 Subsection 15G.

If and when the borrowers to which these individual residential mortgage loans are granted default on interest or repayment obligations, the speed and magnitude of recovery by the lender by executing mortgage rights, depends on federal law and, in addition, state laws that govern the rights of lenders.[56] As now more than a dozen years have passed since the passage of the Dodd-Frank Act, it is worthwhile investigating the extent to which CRAs (the incumbent three and the two entrants) provide consistent ratings given the different levels of creditor protection in the United States. In addition, we seek to analyze if CRAs also take creditor protection into account when constructing the size of private label RMBS deals at issue.

We do so by employing a dataset of virtually all 3,239 private-label RMBS tranches with a total par value of roughly $2 trillion. The tranches included were those originated and issued from the first quarter of 2017 to the third quarter of 2020. We obtained credit rating information of the five CRAs. We use the creditor friendliness score of US state laws constructed by Ghent (2014), a score based on the differences between US state mortgage laws in foreclosures procedures, redemption periods, restrictions on deficiency judgment, and foreclosure moratoria. In addition, our dataset includes several tranche and deal characteristics including tranche size and tranche count per RMBS deal.

In our first set of tests, we investigate whether credit ratings differ between US states given the different levels of creditor protection. Our evidence shows that Moody's and DBRS report lower (higher) credit ratings for tranches issued in states with a lower (higher) creditor protection, but for KBRA, S&P, and Fitch we find no significant relationship. This result is intriguing for two reasons. First, two (Moody's and DBRS) out of five CRAs report significant results, while one might expect that creditor protection for each state is consistently incorporated in the

[56] An RMBS transaction is a financing tool that is backed by a pool of residential mortgage loans. The cash flow to service the securitization debt is based on the underlying pool of residential mortgages, hence, the performance of a tranche of a private-label RMBS depends on the performance of the collateral (residential mortgage loans).

credit rating, irrespective of the CRA. Second, there are three CRAs (Moody's DBRS, KBRA) that explicitly include creditor protection in their rating methodology for US RMBS, however, only Moody's and DBRS show a significant impact in our analysis, KBRA does not. In our second set of tests, we analyze whether higher creditor protection leads new CRAs (DBRS and KBRA combined) to assign, on average, more optimistic ratings than the incumbent CRAs (Moody's, S&P, and Fitch combined). We find that they do. New CRAs are more likely to provide a more optimistic rating compared to incumbent CRAs when the (majority of the) tranche's collateral is located in a state with a low creditor protection. In our third, and final, set of tests we examine whether issuers sell larger tranches in the market in states with stronger creditor protection. We find that issuers indeed construct and sell deals with larger transaction values in more creditor friendly states.

Our study contributes to the literature on creditor protection by identifying how creditor rights in US states impacts the RMBS market. We thereby contribute to a growing body of literature that studies creditor rights (see, e.g., Bae and Goyal, 2009; La Porta et al., 1998; Qian and Strahan, 2007) and its impact on bond (e.g., Mansi et al., 2009) and residential mortgage (e.g., Demiroglu et al., 2014) markets. The salient features of our study are that we examine the impact on the private-label US RMBS market, and that we find that in-country differences in creditor rights are impactful on the RMBS market. To the best of our knowledge, we are the first to link in-country differences in creditor protection related to the credit ratings attached to RMBS tranches. We thereby build upon the study of Ghent (2014) who shows that creditor rights differ between US states and, additionally, we also extent the body of literature on credit rating quality (see, e.g., Fabozzi et al., 2022; Flynn and Ghent, 2018; Griffin et al., 2013; He et al., 2016; Zhou et al., 2017).

The remainder of the paper is organized as follows. In Section 5.2 we examine the existing literature and in Section 5.3 we construct our hypotheses. In Section

5.4 we set out our methodology and in Section 5.5 we discuss the sample construction. In Section 5.6 we provide our analysis and the main empirical results, with Section 5.7 we conclude.

5.2 Literature Review

5.2.1 **Creditor Rights: Cross-Country Differences**

La Porta et al. (1998) show that differences exist in the legal protection of creditors in countries with common-law origin compared to countries with civil-law origin. They also find that common-law origin countries offer stronger legal protection to creditors than civil-law origin countries. Indicators of stronger legal protection in a country are, for example, those with higher-quality institutions and a lower degree of government corruption (La Porta et al., 1998; 2002), and superior courts and insolvency processes (Djankov et al., 2007). There is a well-established strand in the literature that builds upon the work of La Porta et al. (1997; 1998) by providing more evidence on the importance of creditor protection in corporate financings (e.g., Bae and Goyal, 2009; Benmelech and Bergman, 2011; Brockman and Unlu, 2009; Houston et al. 2010; Miller and Reisel, 2012; Qian and Strahan, 2007). These studies show that the willingness of creditors to extend credit and take risks are significantly higher in countries with stronger creditor rights. For example, Qian and Strahan (2007) find evidence that stronger legal protection results in loans with longer maturities and lower loan spreads.

The findings of Bae and Goyal (2009) complement those of Qian and Strahan, as they found that banks react to poor enforceability of contracts by reducing loan sizes and loan maturities. They also report that one of the mitigants to low legal protection in a country is to increase loan spreads. Similarly, Esty and Megginson (2003) find that the size of syndicate loans is positively associated with the strength of creditor rights in a country. Contrary to these findings, Cho et al. (2014) find that stronger creditor protection reduces the amount of corporate debt financing. They argue that firms are demotivated to issue (long-term) debt in countries with stronger creditor protection as stakeholders appear not to consider the risk of losing control during crises.

Most of the literature, suggests that due to greater protection and better enforcement of contracts, it is easier for companies to access capital in common-law countries. These countries are therefore found to have stronger financial systems (La Porta et al., 1998) with higher growth (Houston et al., 2010) than civil-law countries (countries with weaker creditor rights). Additionally, in countries with stronger creditor rights, risk-taking of banks (Houston et al., 2010; Jayaraman and Thakor, 2013), debt issuance of firms (e.g., Djankov et al., 2007; La Porta et al., 1997), and dividend pay-outs (Byrne and O'Connor, 2012) are significantly higher. These arguments notwithstanding, also in countries with higher creditor protection, a sudden increase in the number of foreclosures that disturbs a legal system, such as that observed during the Great Recession, can cause significant delays for creditors to redeem collateral (Ghent, 2014).

5.2.2 **Creditor Rights: Cross-State Differences in US Mortgage Law**

Even though all US states operate under the common-law system, state laws across the United States offer different levels of creditor protection and are based upon different legal theories. Ghent (2014) traces the history of mortgage laws in different US states in terms of foreclosure procedures, redemption periods, restrictions on deficiency judgment, and foreclosure moratoria. She argues that the primary right of the creditor is the capability to foreclose without going to court. State-specific case law dictates whether a creditor is able to foreclose without seeking approval from a judge. Case law derives from a state's early history and foreclosure rules have rarely changed significantly over time. There have been several attempts to create a uniform US mortgage code but without success, so today's mortgage laws continue to consist of a very diverse gamut of state laws (Ghent, 2014). Ghent provides a categorization of laws across US states along the dimensions of (1) lien theory versus title-theory state; (2) mortgage versus deed of trust; (3) power-of-sale foreclosure versus judicial foreclosure; (4) longer statutory/equitable redemption rights; and, (5) deficiency judgement permitted.

First, a lien theory versus a title-theory state relates to two separate legal documents setting out the rules for repayment of the loan. In a title-theory state the debtor gives the creditor possession of the property up until the loan has been repaid. While under lien theory, the creditor only has a lien on the property and the debtor has possession over the property. Hence, a title-theory state is found to offer higher creditor protection than a lien-theory state.

Second, the real estate security instrument can be either a mortgage or a deed of trust. In most US states, a property is funded with a mortgage. But in a few states, a deed of trust is the most common tool wherein the ownership of the property is entrusted to a trustee who is responsible for selling the property in the case of default.

Third, the moment at which the creditor can take possession of the collateral (foreclosure procedures) is a relevant indicator of creditor friendliness. In a state with a judicial foreclosure procedure, the creditor is obliged to go to court before being able to foreclose, while in states with a power-of-sale clause (or in a deed of trust funding), the creditor (or trustee) is able to sell the property without a court approval. Judicial foreclosure is often very timely and costly for creditors and therefore lowers their protection.

Fourth, the redemption right of the debtor to rescue the property by paying the full amount of the loan to the creditor. Important is the period in which the debtor is allowed to apply the redemption rights (the redemption period). The time between the redemption period and foreclosure sale is known as the period providing equitable redemption rights to the borrower. Most US states grant additional time for the borrower after the foreclosure sale to redeem the property, this time period is known as the period of statutory redemption right. A statutory redemption right can be rather problematic for creditors as it influences the value of the property at the auction. Higher redemption rights for borrowers result in lower creditor friendliness.

Finally, some states have laws restricting the creditors from taking possession of debtors' personal belongings. Nevertheless, in most states the creditor is allowed to obtain a deficiency judgement which empowers the creditor to seize any of the debtor's assets, including their salary. In some states, the deficiency judgement is granted automatically when the purchase price of the house is lower than the debt owed, however in most US states the creditor must file a lawsuit. Hence, a state with deficiency judgment is more creditor-friendly than one without (Ghent, 2014).

5.2.3 **Creditor Rights: RMBS Rating Methodologies**

Literature pertaining to creditor rights in the securitization market is rather limited. In their study on European asset-backed securities (ABS), Fabozzi and Vink (2012) show that creditor protection matters for securitization transactions. They state that creditor protection – specifically no automatic stay on the assets[57] – is considered favorable by investors and is expected to be positively reflected in credit ratings, as the creditor has more control over the collateral. However, little attention is given to whether differences in creditor rights are reflected in the credit rating. Gu et al. (2018) are one of the few who find evidence in their study of firm-level data in 51 developed and developing countries, that credit ratings of corporate financings are higher in countries with stronger creditor rights.

[57] An automatic stay prevents secured creditor from obtaining ownership of the security (Qian and Strahan, 2007).

One might expect that the underlying mortgage laws applicable to each state are consistently incorporated in the credit ratings, irrespective of the CRA, as this represents part of the security's risks. That is, CRAs assign a credit rating based on the geographical distribution of the loans by state as disclosed in the prospective supplement available to potential investors. However, to the best of our knowledge, none of the previous studies have analyzed whether CRAs consistently take creditor rights in the United States into account when assigning a credit rating. As a starting point to analyze if they do, we compare and contrast the publicly available credit rating methodologies and find that there are differences among CRAs.

We qualitatively assess the US RMBS credit rating methodology of Moody's (Moody's Investors Service, 2022), S&P (S&P Global Ratings, 2021), Fitch (Fitch Ratings, 2020), DBRS (DBRS Morningstar, 2022), and KBRA (KBRA, 2021)[58]. In order to compare the methodologies, we used the five components of Ghent's credit friendliness score (see section 5.2.2) to analyze what factors of creditor friendliness are incorporated in the CRA's methodology used to determine the credit rating for RMBS tranches. We find that only Moody's, S&P and DBRS consider creditor friendliness per state in their credit rating. All three CRAs only consider one out of the five components in their methodology, namely 'Power-of-sale vs. judicial foreclosure', while the remaining CRAs (Fitch and KBRA) do not consider any of the underling creditor friendliness components in their methodology.[59]

S&P considers the state foreclosure law (judicial/non-judicial) in their borrower's cost/benefit analysis. In their view, liquidation timelines show variability across states based on the specific legal processes for foreclosure. The timelines across states and rating levels are therefore included in their loss severity calculation (S&P Global Ratings, 2021). Moody's adjusts the loan probability of default (PD)

[58] We are only able to review publicly available information on CRAs methodologies. Meaning that there might be a risk that we do not fully capture all input factors used by CRAs in their credit rating models.

[59] We only consider the creditor friendliness components sufficiently incorporated in the methodology when the CRA specifically mentioned that they deviate between the component across US states (e.g., *"we distinguish between properties located in judicial states from those which are not"*).

based on whether the properties are located in judicial states from those which are not (Moody's Investors Service, 2021). Finally, DBRS applies additional stress in their credit rating model depending on, amongst others, the strength of fore closure and liquidation right provisions (DBRS Morningstar, 2022).

To summarize, based on our assessment of the publicly available credit rating methodologies of CRAs, we find that not all CRAs consider the creditor friendliness across US states in their methodologies. Besides, we find inconsistencies between CRAs; Moody's, S&P, and DBRS consider one (out of the five) creditor friendliness component while Fitch and KBRA do not include any. This implies that Moody's, S&P, and DBRS consider creditor friendliness per US state when assigning a credit rating while Fitch and KBRA do not seem to consider it at all.

5.2.4 **Competition and Credit Ratings**

The Great Recession of 2007-2009 was triggered by a great amount of mortgage loans with poor credit quality that were packed and sold to investors. Investors bought tranches on the basis of credit ratings that did not sufficiently reflect the actual credit risk of these high-risk loans. When the market collapsed, investors suffered enormous losses due to defaults among homeowners caused by increasing mortgage rates. Numerous lawsuits by investors touched upon the inaccurate risk assessments by CRAs. It is often argued that the inaccurate risk assessments were caused by the way in which revenue is generated in the credit rating market (see, e.g., He et al., 2016); the CRAs are paid by issuers, not by the investors, giving CRAs a conflict of interest between obtaining revenue and issuing prudent credit ratings. This might give an incentive to CRAs to cater their credit ratings to issuer demands (a better rating) rather than investor needs (a rating representing the actual credit risk). It could also cause rating shopping behavior by issuers: issuers request multiple CRAs to assign a preliminary credit rating, but only select and pay the most optimistic ones (see, e.g., Griffin et al., 2013; He et al., 2016; Zhou et al., 2017; Flynn and Ghent, 2018). Rating shopping and catering behavior might cause overvalued ratings (also referred to as inflated ratings) that do not represent the actual underlying credit risk of a tranche.

Inflated ratings as a result of competition in the credit rating market is found to be even more pronounced for CRAs which are relatively new to the credit rating market, such as DBRS and KBRA. New CRAs seem to offer more optimistic ratings as a competitive strategy against their incumbent, well-established peers, as argued Flynn and Ghent (2018). They find that new entrees assign credit ratings that are several notches higher than those of the incumbent, larger CRAs. Similarly, Bae et al. (2019) and Becker and Milbourn (2011) find that new CRAs tend to provide more optimistic credit ratings compared to the larger ones and that the newer CRAs' credit ratings are less informative. In line with this, Van Breemen et al. (2023) show that competition between large and newer CRAs creates credit rating inconsistencies in the RMBS market.

5.3 Hypotheses Examined

Our assessment of the literature on creditor rights and RMBS transactions led us to create three hypotheses regarding the credit ratings and structure of RMBS transactions. We focus on the US RMBS market specifically. The starting point is that creditor rights for mortgages vary across US states (Ghent, 2014; Gu et al. 2018), thus indirectly providing different levels of protection for investors who invest in RMBS tranches with mortgage loans in these states. First, we are interested if the differences in creditor rights are consistently incorporated by different CRAs in the credit rating for RMBS tranches. Previous studies (e.g., Mansi et al., 2009) show that credit ratings of bonds of firms that are incorporated in states with more restrictive payout statues are higher. Hence, one might expect that CRAs (1) consider the level of creditor protection in their methodology to determine the credit rating for RMBS tranches and (2) that they do so consistently. However, our review of the US RMBS rating methodologies (see section 5.2.3) already shows that only S&P, Moody's and DBRS consider, to some degree, creditor protection per state when assigning credit ratings to RMBS tranche. Fitch and KBRA do not consider any creditor friendliness components in their rating methodology. We therefore hypothesize that creditor protection per state is inconsistently considered by CRAs when assigning credit ratings for RMBS tranches. We construct the following hypothesis:

> *H1. Creditor protection per state is not consistently considered by CRAs in their credit rating.*

Our second hypothesis relates to the impact of creditor rights on competition in the credit rating market. Competition between CRAs in an issuer-pay market framework, incentivizes CRAs to offer credit ratings that cater to issuers' demand (Bolton et al., 2012; He et al., 2016). We hypothesize that new CRAs are more likely to inflate its credit rating as a competitive strategy against their incumbent, more globally established, peers in states that are more creditor friendly. The logic behind this is that in a more creditor-friendly state, one might expect that default risks for the RMBS investor is lower and, consequently, also the chance of reputational losses for CRAs (i.e., via lawsuits of RMBS investors). We expect that new CRAs are more willing to take the risk of providing inflated credit ratings as they compete to gain market share from their more powerful, well-established peers (e.g., Bae et al., 2019; Flynn and Ghent, 2018). We explore these variations and test whether tranches with (the majority of) collateral in a state with higher creditor protection received a more optimistic (inflated) rating of a new CRA compared to its incumbent peer. This leads to our next hypothesis:

> *H2. In a state with higher creditor protection, on average new CRAs tend to report more optimistic ratings than incumbent CRAs for the same tranche.*

Finally, we are interested if issuers take advantage of the level of creditor protection to increase the size of the deal when the underlying collateral is located in states that are more creditor friendly. In conformity with Qian and Strahan (2007) and Bae and Goyal (2009), we expect that stronger creditor rights cause higher risk-taking behavior. We assume that larger deals correspond with more risks as they have a higher amount of underlying loans and collateral, making it more difficult and complex to capture potential risks and returns (e.g., Fahad and Laura, 2017; Furfine, 2014; Jiang et al., 2018; Vink et al., 2021). We therefore expect that issuers are more likely to take the risks associated with larger RMBS deals, when (the majority of) the tranche's collateral is issued in a state with higher creditor protection. This leads us to our final hypothesis:

H3. In a state with higher creditor protection, issuers tend to construct larger RMBS transactions.

5.4 Methodology

We apply three different models to test our hypotheses. First, we use an ordered logit model to estimate the impact of creditor protection in US states on the credit rating assigned by CRAs (Hypothesis 1). To achieve this, we constructed the following model:

$$\begin{aligned} &\textit{Credit Rating (Moody's, S\&P, Fitch, DBRS, KBRA)}_{ijt} = \\ &\alpha_0 + \alpha_1 \textit{ Creditor Friendliness Score}_{s(i)} + \beta \textit{ Tranche, Issuer and Market} \\ &\textit{Controls}_{ijt} + \epsilon_{ijt} \end{aligned} \tag{5.1}$$

The tranches in our data differ by year (t), deal (i), security (j) and state (s). The dependent variable is the *Credit Rating* and the *Creditor Friendliness Score* is the independent variable. The tranche, issuer and market controls include *Log Tranche Value, Log Transaction Value, Tranche Count, Subordination Level, Number of Ratings, Top Ten Issuer, Coupon, and Clustered Collateral*. We control for time-fixed effects. The variable definitions are described in Section 5.5. Next, in order to investigate whether creditor protection of US states has an impact on the difference in disclosed ratings between new and incumbent CRAs at issuance, we estimate the following logit model (Hypothesis 2):

$$\begin{aligned} \textit{Higher by New}_{ijt} = \; & \alpha_0 + \alpha_1 \textit{ Creditor Friendliness Score}_{s(i)} + \beta \textit{ Tranche, Issuer and Market} \\ & \textit{Controls}_{ijt} + \epsilon_{ijt} \end{aligned} \qquad (5.2)$$

The dependent variable *Higher by New* is when a tranche received a more optimistic rating by a new CRA at issuance compared with the incumbent. DBRS and KBRA are representatives of new CRAs and Moody's, S&P, and Fitch as incumbent ones. The independent variable is the *Creditor Friendliness Score* and all controls correspond to those of Equation (5.1).

Finally, we look at the impact of creditor protection of US states on the size and average credit rating of a RMBS transaction (Hypothesis 3). We use ordinary least squares (OLS) regression models with *Log Transaction Value* as the dependent variable and the *Creditor Friendliness Score* as the independent variable, Equation (5.3). The model is specified as follows: 195

$$\begin{aligned} \textit{Log Transaction Value}_{ijt} = \; & \beta_0 + \beta_1 \textit{ Creditor Friendliness Score}_{s(i)} + \beta \textit{ Tranche, Issuer and Market} \\ & \textit{Controls}_{ijt} + \varepsilon_{ijt} \end{aligned} \qquad (5.3)$$

In the OLS regressions, Equation (5.3), we include all controls[60] similar to those of Equations (5.1) and (5.2) and we additionally add *Log GDP* and the *Log House Price* per state. We do so to control for the fact that the average house price and GDP in a state might influence the size of a RMBS transaction. All variables are defined in Section 5.

[60] Note that in Equation (5.3) we use Log Transaction Value as our dependent variable. This variable is therefore not included as a control factor in this model.

5.5 Data

We gather data of RMBS transaction from *Bloomberg* and complement this with (i) Ghent's (2014) creditor-friendliness score for US states, (ii) the average GDP per state from the Bureau of Economic Analysis (2021), and (iii) the average house price of US states from the United States Census Bureau (2020). Our total sample of 3,239 tranches represents virtually all private-label RMBS tranches originated and issued in the US from the first quarter of 2017 to the third quarter of 2020. The total value is roughly USD 2 trillion. We have chosen this timeframe because we want to measure the impact of credit protection in at least five years after the Dodd-Frank Act was implemented.[61] From *Bloomberg* we gathered the available information for each RMBS transaction on collateral location, issuer name and size, credit rating, tranche count, tranche and transaction sizes, coupon rate, subordination level, and reference date.

5.5.1 **Dependent Variables**

Our first dependent variable is the credit rating of CRAs as given by Equation (5.1). To measure the credit rating, we convert the credit ratings to numerical scores. Using S&P's credit rating classification as an example, the numerical scores are as follows: 1 for AAA, 2 for AA+, 3 for AA, 4 for AA-, and so on. We obtained credit rating information from five CRAs: Moody's, S&P, Fitch, DBRS and KBRA. Together these CRAs represent practically all of the credit ratings issued in the US private-label RMBS market. We measure credit rating in two ways: in a combined credit rating and the credit rating of each CRA separately. The combined credit rating measure combines all credit ratings in our sample, irrespectively of the CRA. If a tranche received credit ratings of multiple CRAs, the numerical average of the credit ratings is used. Next, to measure the credit rating of each CRA separately

[61] More specifically, it is the Dodd-Frank Act, 2010, Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Section 941 Subsection 15G.

we construct five different dependent credit rating variables: Moody's credit ratings, DBRS's credit rating, KBRA's credit rating, S&P's credit rating, and Fitch's credit rating. Table 5.1 reports the variable distribution.

The majority (50.76%) of tranches in our sample received a triple A credit rating. The remaining tranches (49.24%) received a very diverse set of credit ratings, ranging from AA+ to C, as reported in Panel B of Table 5.1. Most of these credit ratings are assigned by DBRS (32%), followed by KBRA (30%), Moody's (23%), S&P (12%), and only a small portion by Fitch (3%), Panel C of Table 5.1. In Figure 5.1 we show the distribution of CRAs across US states. Remarkably, of the new entrant CRAs, KBRA assigned most of its ratings in California while DBRS assigned ratings more widespread across states. The vast majority of credit ratings in our sample are assigned in California (92.47%), followed by Florida (4.35%) and New York (1.36%), Panel B of Table 5.2. This is consistent with the figures reported by the National Credit Union Administration (2020) according to which California is the state with the largest percentage of mortgage loans backing private label (i.e., non-agency) RMBS securities, followed by New York and Florida.

In Equation (5.2), we compare the credit ratings of incumbent and new CRAs. The dependent variable *Higher by New* is defined as a dummy variable that takes the value of one if the tranche received a more optimistic credit rating of the newer CRA, for the same tranche, and zero if the credit rating by the incumbent CRA is equal or higher. We compare the credit ratings of Moody's, S&P, Fitch, DBRS and KBRA and define DBRS and KBRA as the new CRAs and Moody's, S&P, and Fitch as the incumbent, globally large CRAs. This distinction is based on the market presence of the CRA in the US credit rating market and the time-period in which the CRA has been active on the rating market. Moody's, S&P and Fitch together assign 92% of the credit ratings in the US market, whilst DBRS have a market share of roughly 3% and KBRA about 0.7%. Notably, the market share of DBRS and KBRA is significantly higher in the US MBS market with 32% and 52% in

2020, respectively (SEC, 2020). Even though the new CRAs have recently gained significant shares in the US MBS market, they are still relatively new to the MBS rating market. KBRA started operating in the MBS market as of 2011 and was able to obtain a market share of approximately 17% in 2012. Morningstar, also a new entrant to the market back then, had a market share of 9% in 2012. DBRS, which operated longer in the market, but was considered a small CRA, had 14% by 2012 (SEC, 2012). Morningstar and DBRS merged in 2019 to DBRS Morningstar (SEC, 2012). We therefore classify them as CRAs which are relatively new and consider them as small CRAs in the total US rating market. Panel D of Table 5.1 reveals that 17.14% of the credit ratings in our sample received a higher rating by a new CRA (DBRS or KBRA) than an incumbent CRA and the majority, 82.86%, received a credit rating that is either equal for incumbent and new CRAs or higher by an incumbent CRA than by a new CRA.

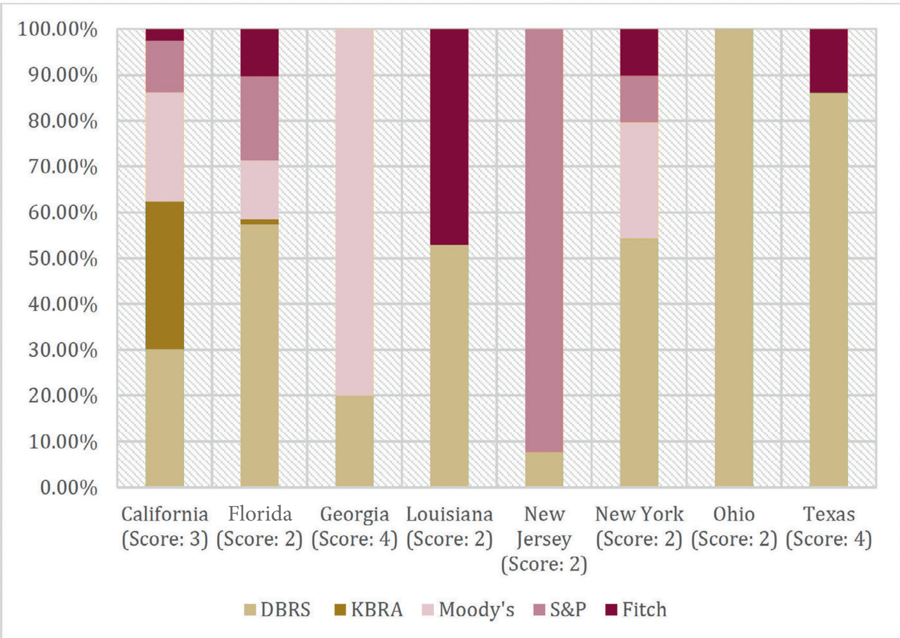


Figure 5.1: Dispersion of CRAs across US states.

This figure illustrates the dispersion of credit ratings assigned by Moody's, S&P, Fitch, DBRS and KBRA across US states. The percentages are calculated by divided the number of tranches rated by a CRA in a specific state by the total number of credit ratings provided in that state. Note that for some states we only have a limited number of observations resulting in less dispersion between CRAs (e.g., Ohio).

Finally, we test the impact of creditor protection on the size of a RMBS deal using Equation (5.3). In Equation (5.3), the dependent variable *Log Transaction Value* equals the natural logarithm of the face value at issuance of the total RMBS transaction in millions of US dollars. The mean *Log Transaction Value* over the whole sample is 21.06.

Table 5.1: Summary statistics of the RMBS tranches.

This table reports summary statistics of RMBS tranches issued in the US market in the first quarter of 2017 up to the third quarter of 2020. 'Credit Rating' are a set of dummies indicating the credit rating of a security at issuance, the ratings are converted in numerical values ranging from 1 (AAA) to 21 (C). 'Creditor Friendliness Score' represent the creditor friendliness of US states' mortgage laws by assigning a score ranging between 4 for most friendly to 0 for least friendly. 'Log Tranche Value' equals the natural logarithm of the tranche value of the security at issuance. 'Log Transaction Value' equals the natural logarithm of the transaction value of the deal at issuance. 'Higher by New' that equals one if a tranche received a more optimistic rating by a new CRA at issuance, and zero if the credit rating of the incumbent CRA is larger or equal. 'Tranche Count' is the sum of all trances in the RMS deal of which the tranche is part of. 'Subordination Level' represent the level of internal credit enhancement supporting such a security within a RMBS, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the RMBS. 'Number of Ratings' is the number of ratings assigned to the tranche at issuance. 'Coupon' is the coupon rate assigned for each tranche at issuance. 'Top Ten Issuer' is a dummy that equal one if the issuer is among the top 10% of issuers in the RMBS market, measured by the value in balance size, and zero otherwise. 'Clustered Collateral' is a dummy variable that equals one if 50% or more of the tranche's collateral is located in one state, and zero if not. 'Log House Price' equals the natural logarithm of the average sales price of new manufactured homes by state in millions of dollars. 'Log GDP' is the natural logarithm of the gross domestic product (GDP) by state in millions of dollars. 'Year' represents a set of dummy variables that correspond to the year in which the RMBS was issued. Panel A presents the overall summary statistics; Panel B presents the detailed distribution of the 'Credit Ratings' in our sample; Panel C the distribution of credit ratings per CRA; and Panel D the detailed distribution of 'Higher by New'.

Panel A: Overall Summary Statistics

Variable	N	Mean	Median	Std	P25	P75
Credit Rating	3,239	4.56	1.00	4.72	1.00	8.00
Creditor Friendliness Score	3,239	2.95	3.00	0.27	3.00	3.00
Log Tranche Value	3,239	17.20	17.08	1.50	16.17	18.16
Log Transaction Value	3,239	21.06	21.04	0.57	20.78	21.32
Higher by New	3,239	0.17	0.00	0.38	0.00	0.00
Tranche Count	3,239	17.41	17.00	5.36	13.00	21.00
Subordination Level	3,239	0.42	0.41	0.31	0.11	0.71
Number of Ratings	3,239	1.57	2.00	0.62	1.00	2.00
Coupon	3,239	2.73	3.10	1.65	0.50	4.00
Top Ten Issuer	3,239	0.63	1.00	0.48	0.00	1.00
Clustered Collateral	3,239	0.17	0.00	0.38	0.00	0.00
Log House Price	3,239	11.62	11.63	0.10	11.61	11.68
Log GDP	3,239	14.85	14.90	0.28	14.90	14.95
Year	3,239	2019	2019	0.90	2018	2019

Panel B: Distribution of Credit Ratings

Credit Rating	Numerical Value	Freq.	Percentage
AAA	1	1644	50,76%
AA+	2	120	3,70%
AA	3	212	6,55%
AA-	4	83	2,56%
A+	5	78	2,41%
A	6	202	6,24%
A-	7	56	1,73%
BBB+	8	54	1,67%
BBB	9	192	5,93%
BBB-	10	68	2,10%
BB+	11	63	1,95%
BB	12	176	5,43%
BB-	13	37	1,14%
B+	14	65	2,01%
B	15	156	4,82%
B-	16	26	0,80%
CCC+	17	1	0,03%
CCC	18	3	0,09%
CCC-	19	0	0,00%
CC	20	2	0,06%
C	21	1	0,03%
Total		3,239	100%

Panel C: Distribution of CRAs by state

	California	Florida	Georgia	Louisiana	New Jersey	New York	Ohio	Texas	Total	Percent
DBRS	1426	112	1	9	1	32	3	31	1615	32%
KBRA	1526	2	0	0	0	0	0	0	1528	30%
Moody's	1133	25	4	0	0	15	0	0	1177	23%
S&P	533	36	0	0	12	6	0	0	587	12%
Fitch	122	20	0	8	0	6	0	5	161	3%
Total	4740	195	5	17	13	59	3	36	5,068	100%

Panel D: Higher by New

	Freq.	Percent
1 (Higher by small)	555	17.14
0 (Higher by large or equal)	2684	82.86
Total	3,239	100%

5.5.2 **Independent Variable**

To measure creditor protection in US states we use the *Creditor Friendliness Score* constructed by Ghent (2014). The *Creditor Friendliness Score* is our key independent variable throughout all regression models. Ghent's score measures the extent to which states' current mortgage laws in the US are creditor friendly. The classification is based on the laws applicable to residential loans that were issued in 2010 or later. The score ranges from 0 to 1 and is based on the dimensions[62] that are explained in section 5.2.2. Points are awarded as follows by Ghent: 2 for the foreclosure procedure used, 1 for creditor-friendly forms of judicial foreclosure procedures and minimal restrictions, 2 points for states permitting power-of-sale foreclosures. A score of 4 is assigned for the most creditor-friendly state regimes and a score of 0 for the least creditor-friendly laws (Ghent, 2014). We link this score to the underlying collateral information as reported in *Bloomberg*. The collateral information only reports the state in which the majority of the tranche's collateral is located (e.g., 60% located in California), so we link the tranche with the state in which the majority of its collateral is located.

Our study is unique as the majority of empirical studies[63] that investigate creditor rights use the creditor rights index constructed by La Porta et al. (1997), or the updated version of Djankov et al. (2007), that estimate the creditor protection of a specific country but do not differentiate between country regions. Hence, these indices do not allow us to compare *in-country* differences between US states as each country receives only one creditor protection score without deviating between country regions (e.g., the United States received a creditor protection score for the whole country only, no division between states has been made).

[62] The five dimensions are (i) lien theory versus title-theory state, (ii) mortgage versus deed of trust, (iii) the power-of-sale foreclosure versus judicial foreclosure, (iv) longer statutory/equitable redemption rights, and (v) deficiency judgement permitted.
[63] See, for example, Qian and Strahan (2007), Bae and Goyal (2009), and Cho et al. (2014).

However, as creditor protection of mortgage laws significantly differs across states (Ghent, 2014), a score that deviates between creditor protection across states seems more suitable to assess creditor protection in the Unites States.

We report the creditor friendliness scores for all US states constructed by Ghent in Panel A of Table 5.2 and visualize these scores in Figure 5.2. Panel B of Table 5.2 provides the creditor-friendliness scores of states in our sample after we applied all our filters. The majority of the tranche's collateral in our sample (92.47%) is located in California, with a relative high creditor-friendliness score of 3. Two states in our sample, Georgia and Texas, received the highest score of 4, comprising 0.12% and 0.96% respectively. The remaining states received a relative low friendliness score of 2 for Florida (4.35%), Louisiana (0.28%), New Jersey (0.37%), New York (1.36%), and Ohio (0.09%). To avoid sample bias, we run robustness analyses (see section 5.6.4) in which we randomly reduce the tranches with exposure to California. For example, resulting in a sample with 64.79% of the tranche's exposure to California, 20.35% to Florida and the remaining to New York (6.35%), Texas, (4.47%), New Jersey (1.73%), Louisiana (1.30%), Georgia (0.58%) and Ohio (0.43%).

5.5.3 **Control Variables**

To control for features of the underlying RMSB deal we include a number of control variables: tranche and transaction size; subordination level of the tranche; number of tranches in a corresponding RMBS deal; number of credit rating assigned to the tranche; the tranche's coupon rate; size of the issuer; geographic dispersion of the underlying collateral; year of issuance; and the average house price and GDP in a given state. The descriptive statistics and variable distributions are presented in Panel A of Table 5.1. *Log Tranche Value* is the natural logarithm of the par value of a tranche at issuance. The mean *Log Tranche Value* in our total sample is 17.20. *Subordination Level* is the level of credit support for a tranche, indicating the percent of cushioning in the capital structure of a RMBS deal against credit losses that a specific tranche could suffer. The cushioning is provided by the additional tranches in the RMBS deal that are subordinated to the tranche in question. The mean subordination level in our sample is 0.42%. Tranche count corresponds to the total number of tranches in the RMBS deal of which the tranche belongs to. In our sample, the average number of tranches per RMBS deal is 17.41. The *Number of Ratings* is the number of credit ratings attached to a tranche at issuance, on average a tranche received 1.57 ratings in our sample. *Coupon* is the coupon rate assigned for each tranche at issuance, in our sample the mean coupon rate is 2.73%.

We also control for issuer size. To do so, we use a dummy variable, *Top Ten Issuer*, that equals one if the issuer is among the top 10% of issuers measured using the global RMBSs market share, and zero if the issuer is among the remaining 90%. To measure the dispersion of the tranche's collateral, we control for the extent to which the tranche's collateral is located in one state. *Clustered Collateral* is a dummy variable that equals one if 50% or more of the tranche's collateral is located in one state, and zero if not. The mean clustered collateral in our sample is 0.17%. In Equation (5.3), we also include the average house price in each state and the GDP by state, to control for possible biases in the transaction size of a deal when certain states have higher house prices of GDP on average. '*Log House Price'* equals the natural logarithm of the average sales price of new manufactured homes by state in millions of dollars. The average *Log House Price* in our sample is 11.62. The '*Log GDP'* is the natural logarithm of the gross domestic product (GDP) by state in millions of dollars. The average *Log GDP* in our sample is 14.85.

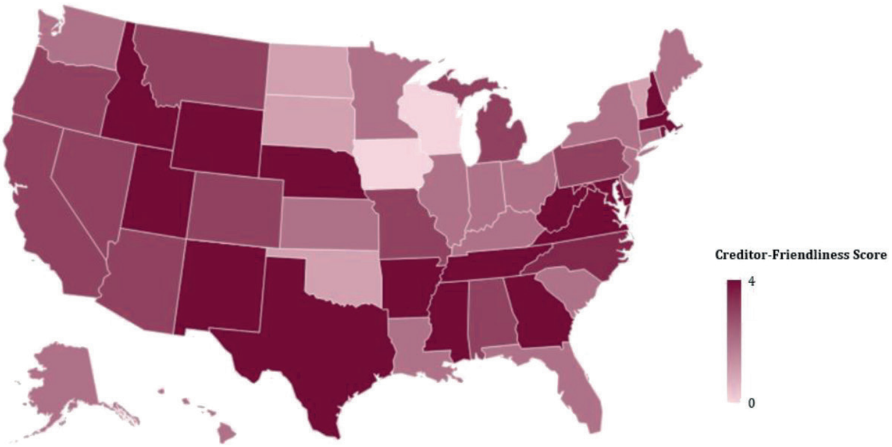


Figure 5.2: Creditor friendliness score of all US states.

This figure illustrates the creditor friendliness score of all US states' mortgage laws as defined by Ghent (2014). A score of 4 is given to the states with most creditor-friendly laws and a score of 0 to states with the least creditor-friendly laws. A score of 2 is rewarded when the power-of-sale foreclosure is the usual procedure in a state. A score of 1 if deficiency judgements are permitted without substantial restrictions and a score of 1 is given if statutory redemption is usually less than 6 months. The scores are listed in Panel A of Table 5.2.

Table 5.2: Creditor friendliness score of US states' mortgage laws.

This table reports the creditor friendliness score of US states' mortgage laws as defined by Ghent (2014). A score of 4 is given to the states with most creditor-friendly laws and a score of 0 to states with the least creditor-friendly laws. A score of 2 is rewarded when the power-of-sale foreclosure is the usual procedure in a state. A score of 1 if deficiency judgements are permitted without substantial restrictions and a score of 1 is given if statutory redemption is usually less than 6 months. Panel A presents the creditor-friendliness score of all US states as defined by Ghent (2014) and Panel B of the tranche's collateral in our sample.

Panel A: Creditor Friendliness Score of US states' mortgage laws (Ghent, 2014)

State	Score	State	Score
Alaska	2	Michigan	3
California	3	Ohio	2
Hawaii	2	Wisconsin	0
Oregon	3	Alabama	3
Washington	2	Kentucky	2
Arizona	3	Mississippi	4
Colorado	3	Tennessee	4
Idaho	4	New Jersey	2
Montana	3	New York	2
Nevada	3	Pennsylvania	3
New Mexico	4	Delaware	3
Utah	4	District of Columbia	4
Wyoming	4	Florida	2
Iowa	0	Georgia	4
Kansas	2	Maryland	4
Minnesota	2	North Carolina	3,5
Missouri	3	South Carolina	2
Nebraska	4	Virginia	4
North Dakota	1	West Virginia	4
South Dakota	1	Connecticut	2
Arkansas	4	Maine	2
Louisiana	2	Massachusetts	4
Oklahoma	1	New Hampshire	4
Texas	4	Rhode Island	4
Illinois	2	Vermont	1
Indiana	2		

205

Panel B: Creditor-friendliness of tranche's collateral in our sample

State	Friendliness score	No. of tranches	% of sample
California	3	2995	92,47%
Florida	2	141	4,35%
Georgia	4	4	0,12%
Louisiana	2	9	0,28%
New Jersey	2	12	0,37%
New York	2	44	1,36%
Ohio	2	3	0,09%
Texas	4	31	0,96%
Total		3,239	100,00%

5.6 Results

In this section, we examine the impact of creditor protection on the credit ratings disclosed and on the deal size of RMBS transactions, both at issuance. In section 5.6.1, we start by analyzing the extent to which CRAs consider the creditor protection of US states' mortgage laws in their credit rating. We seek to analyze if creditor protection impacts the credit rating and whether this is consistently considered amongst different CRAs. In section 5.6.2, we analyze if the two new CRAs are more likely to inflate its credit rating, compared to the incumbent three, when the tranche is issued in a more creditor-friendly state. Finally, in section 5.6.3, we examine if creditor protection of US states' mortgage laws has an impact on the deal size of RMBS.

Table 5.3 provides the results for Equation (5.1), the *Credit Rating* is the dependent variable and the *Creditor Friendliness Score* the independent variable. In Table 5.4, we repeat the analysis of Table 5.3 but replace our combined measure for credit rating with the credit rating of each CRA separately: *DBRS, Moody's, KBRA, S&P,* and *Fitch*. We do so to analyze whether CRAs use a different approach when considering creditor-friendliness in their credit rating (H1). Next, we test the impact of creditor protection on the rating difference between new and incumbent CRA, where *Higher by New* is the dependent variable and the *Creditor Friendliness Score* the independent variable (H2). These results are reported in Table 5.5 and are based on Equation (5.2). We report the results of Equation (5.3) in Table 5.6, the *Log Transaction Value* is the dependent variables, and the *Creditor Friendliness Score* is the primary independent variable (H3). In Table 5.7, we provide several robustness analyses to all our models.

5.6.1 **Creditor rights and credit ratings**

The results of the ordered logit regressions with the combined credit rating as dependent variable are reported in Table 5.3. The combined credit rating measure combines all credit ratings in our sample, irrespective of the CRA that assigned the rating. In column (1) of Table 5.3, the odds ratio of the *Creditor Friendliness Score* is negative and highly significant (with odds of -1.29), indicating that a one standard deviation increase in the creditor friendliness score decreases the odds of experiencing a stricter rating (further from AAA). In other words, if (the majority of) the tranche's collateral is issued in a more creditor-friendly state, than this tranche received a more optimistic rating (closer to AAA), compared to a state that is less creditor-friendly. A result that builds upon the research of Gu et al. (2018) who show that credit ratings of firms are more optimistic in countries with higher creditor rights. We find similar results when we include several tranche, issuer and market controls in columns (2) to (5). In column (2), we add our control variables *Tranche Count* and *Subordination Level* to our model. The coefficient of our key independent variable, *Creditor Friendliness Score* stays negative and highly significant, with the odds of −1.24 (z-statistics of -9.06). We obtain similar results when we include all our control variables, including *Year* fixed effects, in our model in column (5). By including all our controls in column (5), the Pseudo R^2 reveals a significant higher explanatory power of 29.6%. Hence, our model is robust when we rotationally include several control variables and these controls explain a significant proportion of variation in our dependent variable, as denoted by the R^2.

We now move to the ordered logit regressions in Table 5.4, in which we replace our combined credit rating measure with those of each CRA separately. The credit ratings of DBRS are reported in column (1), KBRA in column (2), Moody's in column (3), S&P in column (4) and Fitch in column (5). Based on our review of the credit rating methodologies (section 5.2.3), we expect that Moody's, S&P and DBRS consider the creditor friendliness per state, while Fitch and KBRA do not at all. In line with this, in Table 5.4 we observe some remarkable differences between CRAs using ordered logit regressions. For DBRS and Moody's we find significant negative coefficients for our *Creditor Friendliness Score*. A result consistent with our combined credit rating measure in Table 5.3. So, a one-standard deviation increase in the creditor friendliness score decrease the odds of experiencing a stricter rating (further away from AAA) of DBRS and Moody's, with odds of -0.90 and -3.68, respectively, as shown in columns (1) and (3). Interestingly, the odds of Moody's reporting a more optimistic rating is four times higher than DBRS. For KBRA, S&P and Fitch, however, we find no relation at all between the creditor-friendliness score and their credit rating, columns (2), (4), and (5) in Table 5.4. Apart from S&P, these results are in line with our review of the credit rating methodologies where we showed that Fitch and KBRA do not take creditor friendliness per state into account, while the remaining CRAs (Moody's, S&P, and DBRS) do.

In sum, the results of Table 5.3 suggest that credit ratings differ, on average, between US states with different levels of creditor protection. We show that CRAs disclose better credit ratings for tranches issued in states with higher creditor friendliness scores. At the same time, if we look at each CRA separately in Table 5.4, we observe that this is only true for Moody's and DBRS, while we find no such relation for KBRA, S&P and Fitch. However, it should be noted that it is difficult to determine the exact reason for our findings as it could also be that the underlying pool is, on average, riskier in states with lower creditor protection.[64] Overall, our results support our first hypothesis (H1) in which we posit that creditor friendliness per US state is considered in an inconsistent way between CRAs when they assign credit ratings to RMBS tranches.

5.6.2 **Creditor rights and competition**

In this section, we analyze if DBRS and KBRA (new CRAs) are more likely to assign optimistic (or inflated) ratings compared to Moody's, S&P, and Fitch (incumbent

[64] Given data limitations, we cannot control for the inherent risk of the underlying pool of the securitization transaction.

CRAs), on average for the same tranche, when a tranche is issued in a state with higher creditor protection. The results of the logit regressions are provided in Table 5.5, with the discrepancy between the credit rating of new and incumbent CRAs, *Higher by New*, as the dependent variable. In column (1) of Table 5.5 we find that the odds ratio of the *Creditor Friendliness Score* is positive and significant (with odds of 0.66), indicating that a one standard deviation increase in the creditor friendliness score increases the odds of experiencing a higher rating by a new CRAs (DBRS or KBRA). In the consecutive columns we include our tranche, issuer and market controls and find similar positive significant results, columns (2) to (5). Column (5) represents our full model, including all control variables. We show that the coefficient of our key independent variable, *Creditor Friendliness Score*, remains positive and highly significant, with the odds of 0.94 (z-statistics of 2.95), in our full model, column (5).

These results suggest that new CRAs are more likely to provide a more optimistic credit rating, on average for the same tranche, than incumbent CRAs when (the majority of) the tranche's collateral is issued in a creditor-friendly state. This finding is in line with our hypothesis that a more creditor friendly state provides a safer environment for a new CRA to assign a better credit rating to the liking of the issuer (rating inflation), while in a state with lower creditor-friendliness, the risks for reputational losses are too high to do so. The findings in Table 5.5 suggest that H2, in which we posit that in a state with higher creditor-friendliness new CRAs more likely report optimistic ratings than incumbent CRAs, is supported.

5.6.3 **Creditor rights and issuers**

In this section, we investigate whether issuers consider the protection of creditors when they construct an RMBS deal. We are specifically interested if issuers are willing to take more risks by constructing a larger deal (in terms of transaction size) for an RMBS transaction that is issued in a more creditor friendly state. The results of the OLS regressions of the *Creditor Friendliness Score* on the RMBS transaction size are reported in Table 5.6. When we look at the results for *Log Transaction Value,* we find a significant positive *Creditor Friendliness Score* coefficient of 0.45 (*t-stat*= 7.21) in column (1). This means that if (the majority of) the tranche's collateral is located in a creditor-friendly state than the transaction value of the RMBS is on average larger. This result remains consistent when we include the controls in columns (2) to (4). We show our full model, including all control variables, in column (4). We find consistent positive and highly significant results for *Creditor friendliness Score*, with a coefficient of 0.54 (*t-stat*= 3.88). Hence, the RMBS transaction value (balance amount of all tranches combined of one deal) increases when the tranche is issued in a more creditor-friendly state. This indicates that issuers construct a larger deal when the state is more creditor friendly. One might argue that issuers take advantage of the heterogeneity in creditor protection between states in constructing deals. This is in line with H3, in which we posit that in a state with higher creditor protection, issuers tend to construct larger RMBS transactions.

5.6.4 **Robustness analyses**

We perform several robustness analyses to avoid potential sample and omitted variable bias. To reduce potential sample bias, we randomly reduce the sample of tranches where (the majority of) the tranche's collateral is located in California. We do so as the majority of tranches in our sample have exposure to California (92.47%). Therefore, we repeat our analyses in Tables 5.3 (Equation 5.1), 5.5 (Equation 5.2), and 5.6 (Equation 5.3) but now only include 15% of the California sample.[65] The results are reported in Table 5.7, where column (1) provides the results using Equation (5.1), column (3) using Equation (5.2), and column (5) using Equation (5.3). We show that our results remain robust when using only a (randomly selected) subset of our California sample.

[65] Similar results are obtained when we use a different randomly selected portion of the California sample.

Next, to reduce potential omitted variable bias, we have included additional control variables to our models. First, we now also include '*House Price*' and '*GDP*' as control variables in Equations (5.1) and (5.2). In addition, we include '*Issuer*' and '*State*' controls to all our models. The issuer represents the issuer of the securitization transaction and the state represents the state in which the (majority of the) transaction's collateral is located. We report the results with all the additional control variables in columns (2), (4), and (6) of Table 5.7. Column (2) shows the results for Equation (5.1), column (4) for Equation (5.2) and column (6) for Equation (5.3). We show that our results also remain robust when we include several additional control variables to our models.

Table 5.3: Ordered logit regressions of creditor friendliness on credit rating.

This table reports ordered logit regressions of the creditor friendliness score on the credit rating of RMBS securities for the US market, controlled for deal-level characteristics, issuer characteristics and market conditions. We collected the full sample of RMBS securities as reported in Bloomberg between 2017 and 2020. The tranches in our sample received at least one rating from Moody's, S&P, Fitch, DBRS or KBRA. The dependent variable 'Credit Rating' represents the numerical value of the credit rating assigned to a tranche at issuance. The numerical credit rating values range from 1 (AAA) to 21 (C). The key independent variable is 'Creditor Friendliness score' representing the creditor friendliness of US states' mortgage laws by assigning a score ranging between 4 for most friendly to 0 for least friendly. 'Log Tranche Value' equals the natural logarithm of the tranche value of the security at issuance. 'Log Transaction Value' equals the natural logarithm of the transaction value of the deal at issuance. 'Higher by New' that equals one if, at issuance, a tranche received a more lenient (optimistic) rating by the new CRA, and zero otherwise. 'Tranche Count' is the sum of all trances in the RMS deal of which the tranche is part of. 'Subordination Level' represent the level of internal credit enhancement supporting such a security within a RMBS, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the RMBS. 'Number of Ratings' is the number of ratings assigned to a specific tranche at issuance. 'Coupon' is the coupon rate assigned for each tranche at issuance. 'Top Ten Issuer' is a dummy that equal one if the issuer is among the top 10% of issuers in the RMBS market, measured by the value in balance size, and zero otherwise. 'Clustered Collateral' is a dummy variable that equals one if 50% or more of the tranche's collateral is located in one state, and zero if not. 'Year' represents a set of dummy variables that correspond to the year in which the RMBS was issued. Z-statistics are provided in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
Creditor Friendliness Score	-1.29***	-1.24***	-0.99***	-1.07***	-1.14***
	(-9.44)	(-9.06)	(-7.17)	(-7.67)	(-8.07)
Log Tranche Value	-1.33***	-1.79***	-1.51***	-1.52***	-1.56***
	(-36.36)	(-36.47)	(-30.43)	(-30.28)	(-30.57)
Log Transaction Value	0.56***	1.46***	1.45***	1.44***	1.46***
	(7.45)	(19.43)	(19.38)	(18.90)	(19.00)
Tranche Count		-0.29***	-0.24***	-0.24***	-0.25***
		(-31.13)	(-25.52)	(-25.42)	(-25.90)
Subordination Level		-0.68***	-1.29***	-1.37***	-1.55***
		(-4.65)	(-8.38)	(-8.79)	(-9.82)
Number of Ratings			-0.28***	-0.33***	-0.28***
			(-4.19)	(-4.76)	(-3.92)
Coupon			0.68***	0.68***	0.70***
			(19.16)	(19.11)	(19.45)
Top Ten Issuer				0.13	0.22**
				(1.57)	(2.51)
Clustered Collateral				0.51***	0.51***
				(4.87)	(4.85)
Year	N	N	N	N	Y
Observations	3,239	3,239	3,239	3,239	3,239
Pseudo R2	0.157	0.254	0.284	0.286	0.296

Table 5.4: Ordered logit regressions of creditor friendliness on different CRAs.

This table reports ordered logit regressions of the creditor friendliness score on the credit rating of RMBS securities for the US market, controlled for deal-level characteristics, issuer characteristics and market conditions. We collected the full sample of RMBS securities as reported in Bloomberg between 2017 and 2020. The tranches in our sample received at least one rating from Moody's, S&P, Fitch, DBRS or KBRA. The dependent variable is the numerical values of a credit rating of the tranches at issuance for each CRA separately: DBRS, KBRA, Moody's, S&P, and Fitch. The numerical credit rating values range from 1 (AAA) to 21 (C). The key independent variable is 'Creditor Friendliness score' representing the creditor friendliness of US states' mortgage laws by assigning a score ranging between 4 for most friendly to 0 for least friendly. The remaining variables are defined in Table 5.3. Z-statistics are provided in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	DBRS	***KBRA***	***Moody's***	***S&P***	***Fitch***
	(1)	(2)	(3)	(4)	(5)
Creditor Friendliness Score	-0.90***	5.65	-3.68***	-0.33	-0.12
	(-5.55)	(0.01)	(-9.88)	(-1.04)	(-0.29)
Log Tranche Value	-1.69***	-2.39***	-2.02***	-1.87***	-2.72***
	(-22.11)	(-20.67)	(-21.05)	(-15.19)	(-9.09)
Log Transaction Value	1.27***	1.79***	1.23***	1.27***	2.79***
	(12.04)	(8.80)	(7.41)	(7.91)	(6.49)
Tranche Count	-0.26***	-0.24***	-0.21***	-0.14***	-0.31***
	(-17.95)	(-12.58)	(-9.00)	(-4.80)	(-6.01)
Subordination Level	-1.53***	-1.18***	-2.37***	-1.24***	0.63
	(-6.79)	(-3.87)	(-8.17)	(-2.79)	(0.78)
Number of Ratings	-0.44***	-0.13	-1.12***	-0.90***	-0.77
	(-4.03)	(-1.04)	(-5.32)	(-4.05)	(-1.42)
Coupon	0.62***	0.78***	0.51***	0.99***	0.42***
	(12.32)	(11.75)	(7.15)	(11.03)	(2.64)
Top Ten Issuer	0.36***	0.36**	1.01***	0.16	2.48***
	(3.08)	(2.20)	(6.36)	(0.90)	(4.72)
Clustered Collateral	0.28*	1.62***	1.37***	-0.08	0.02
	(1.85)	(8.88)	(5.50)	(-0.44)	(0.02)
Year	Y	Y	Y	Y	Y
Observations	1,615	1,528	1,177	587	161
Pseudo R2	0.290	0.425	0.313	0.316	0.332

Table 5.6: OLS regressions of creditor friendliness on RMBS transaction value.

This table reports OLS regressions of the creditor-friendliness score on the size of RMBS transactions for the US market, controlled for deal-level characteristics, issuer characteristics and market conditions. We collected the full sample of RMBS securities as reported in Bloomberg between 2017 and 2020. The tranches in our sample received at least one rating from Moody's, S&P, Fitch, DBRS or KBRA. The dependent variable 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance. The key independent variable is 'Creditor Friendliness Score' representing the creditor friendliness of US states' mortgage laws by assigning a score ranging between 4 for most friendly to 0 for least friendly. 'Log House Price' equals the natural logarithm of the average sales price of new manufactured homes by state in millions of dollars. 'Log GDP' is the natural logarithm of the gross domestic product (GDP) by state in millions of dollars. The remaining variables are defined in Table 5.3. White (1980) heteroskedasticity-adjusted t-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Creditor Friendliness Score	0.45***	0.41***	0.41***	0.54***
	(7.21)	(6.66)	(6.62)	(3.88)
Tranche Count	0.21***	0.19***	0.19***	0.19***
	(17.66)	(16.84)	(16.81)	(15.68)
Log Tranche Value	0.04***	0.04***	0.04***	0.04***
	(18.34)	(15.59)	(15.61)	(18.22)
Subordination Level	-0.02	0.04	0.04	0.05
	(-0.56)	(1.12)	(1.14)	(1.24)
Number of Ratings		0.02	0.03	0.04**
		(1.44)	(1.49)	(2.09)
Coupon		-0.04***	-0.04***	-0.04***
		(-5.17)	(-5.17)	(-5.26)
Top Ten Issuer		0.20***	0.20***	0.20***
		(11.53)	(11.43)	(11.23)
Clustered Collateral			-0.007	-0.0002
			(-0.36)	(-0.001)
House Price				-0.89***
				(-2.96)
GDP				0.09
				(0.69)
Credit rating	Y	Y	Y	Y
Year	Y	Y	Y	Y
Observations	3,239	3,239	3,239	3,239
R-squared	0.266	0.298	0.298	0.306
Adjusted R-squared	0.260	0.291	0.291	0.299

Table 5.7: Robustness analyses.

This table reports robustness analyses of the creditor-friendliness score on our three key independent variables: Credit Rating (columns 1 and 2), Higher by New (columns 3 and 4) and Transaction Value (columns 5 and 6). Columns (1) and (2) report ordered logit regressions of the creditor-friendliness score on the credit rating at issuance (similar to Table 5.3). Columns (3) and (4) report logit regressions of the creditor-friendliness score on the rating differences between new and incumbent CRAs (similar to Table 5.5). Columns (5) and (6) report ordinary least squares regressions of the creditor-friendliness score on the size of RMBS transactions (similar to Table 5.6). Columns (1), (3) and (5) represent the results of our randomly reduced sample (15% of California only). The following additional controls are included for robustness purposes in columns (2), (4) and (6): 'House Price', 'GDP', 'Issuer', and 'State'. 'Issuer' represents the issuer of the securitization tranche and 'State' represents the state in which the (majority of the) transaction's collateral is located. The remaining variables are defined in Table 5.3. (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	Credit Rating		**Higher by new**		**Log Transaction Value**	
	(1)	(2)	(3)	(4)	(5)	(6)
Creditor Friendliness Score	-0.71***	-0.69***	1.16***	1.29**	0.47***	0.54***
	(-3.93)	(-2.67)	(2.74)	(0.84)	(3.71)	(3.88)
Log Tranche Value	-1.57***	-1.58***	-0.26	-0.70***	0.26***	0.19***
	(-13.81)	(-30.58)	(-1.28)	(-9.86)	(9.98)	(15.68)
Log Transaction Value	1.42***	1.46***	0.30	0.56***		
	(10.27)	(18.49)	(0.97)	(3.89)		
Tranche Count	-0.23***	-0.24***	0.09**	-0.02	0.04***	0.04***
	(-12.27)	(-24.04)	(2.23)	(-1.16)	(6.65)	(18.22)
Subordination Level	-0.96***	-1.49***	0.31	-0.73***	-0.10	0.05
	(-2.88)	(-9.26)	(0.45)	(-3.13)	(-0.93)	(1.24)
Number of Ratings	-0.47***	-0.26***	3.34***	2.41***	0.07*	0.04**
	(-3.09)	(-3.71)	(7.71)	(17.21)	(1.96)	(2.09)
Coupon	0.75***	0.70***	-0.13	0.22***	-0.06***	-0.04***
	(8.78)	(19.28)	(-0.89)	(4.01)	(-2.80)	(-5.26)
Top Ten Issuer	0.037	0.21**	0.76**	0.40***	0.27***	0.20***
	(0.20)	(2.34)	(2.19)	(3.01)	(6.13)	(11.23)
Clustered Collateral	-0.03	0.51***	-0.66	0.10	0.04	0.00
	(-0.10)	(4.84)	(-1.47)	(0.67)	(0.63)	(0.00)
House Price		-1.65		8.19	-0.95***	-0.89***
		(-1.25)		(0.90)	(-2.97)	(-2.96)
GDP		-0.08		0.03	0.18	0.09
		(-0.27)		(0.04)	(1.48)	(0.69)
Issuer	N	Y	N	Y	N	Y
State	N	Y	N	Y	N	Y
Credit rating	N	N	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Observations	692	3,239	692	3,239	692	3,239
Pseudo R-squared	0.269	0.297	0.428	0.315		
Adjusted R-squared					0.413	0.299

5.7 Conclusion

Improving the market structure and transparency of information in the securitization market has received considerable attention from academics and regulators in the last decade. The question remains whether investors are indeed channeled with more accurate information on the risks they are exposed to and if issuers consider these risks properly when constructing higher risk deals. We analyzed 3,239 RMBS tranches that were originated and sold from the first quarter of 2017 to the third quarter of 2020 to study the impact of creditor rights in US states on the credit ratings and size of RMBS transactions.

We provide three striking results. First, we find that credit ratings of CRAs differ between US states that have different levels of creditor protection. Specifically, we find inconsistency between CRAs: Moody's and DBRS do provide better credit ratings on average for RMBS in states with higher creditor protection (closer to AAA). However, we find no significant relation for KBRA, S&P, and Fitch. Second, our findings show that there exists inconsistency between those CRAs traditionally operating in the market (Moody's, S&P, and Fitch) and those who are relatively new (DBRS and KBRA). New CRAs tend to provide more optimistic ratings, on average, than the incumbent ones when the (majority of the) tranche's collateral is located in a creditor friendly state. Perhaps, as per our second hypothesis, new CRAs take advantage of the lower-risk environment that comes with higher creditor protection and are consequently bolder in assigning more optimistic ratings. Finally, we find that issuers appear to be aware of the level of creditor protection when constructing RMBS deals as they tend to construct larger RMBS deals when the (majority of the) tranche's collateral is located in a creditor friendly state. This indicates that issuers may be sagaciously seeking to optimize their risk-return levels (in terms of transaction size) by exploiting the differences in creditor protection across US states.

These results suggest that regulators and investors should – still, after the lessons learnt from the Global Financial Crisis and in spite of the improvements sought via the implementation of the Dodd-Frank Act – wisely interpret the quality of US RMBS credit ratings when it comes to the level of creditor protection. Strikingly, creditor protection is not only reflected lowly by CRAs in assigning their credit rating, but competition between CRAs also seems to play a significant role when assigning a credit rating. One might expect that CRAs assign a credit rating based solely on the underlying credit risk of the tranche (including creditor protection), while our results show that CRAs also take advantages of a lower-risk environment by providing more optimistic ratings, most likely to gain or retain market share.

References

Adelson, M. (2020). The mortgage meltdown and the failure of investor protection. *The Journal of Structured Finance, 26*(1), 63–86. https://doi.org/10.3905/jsf.2020.1.095

Bae, K. H., Driss, H., & Roberts, G. S. (2019). Does competition affect ratings quality? Evidence from Canadian corporate bonds. *Journal of Corporate Finance, 58*, 605–623. https://doi.org/10.1016/j.jcorpfin.2019.07.009

Bae, K., & Goyal, V. K. (2009). Creditor rights, enforcement, and bank loans. *The Journal of Finance*, *64*(2), 823–860. https://doi.org/10.1111/j.1540-6261.2009.01450.x

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, *101*(3), 493–514. https://doi.org/10.1016/j.jfineco.2011.03.012

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, *67*(1), 85–111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Benmelech, E., & Bergman, N. K. (2011). Vintage capital and creditor protection. *Journal of Financial Economics, 99*(2), 308–332. https://doi.org/10.1016/j.jfineco.2010.09.004

Breemen, V. van, Fabozzi, F. J., & Vink, D. (2023). Intensified competition and the impact on credit ratings in the RMBS market. *Financial Markets, Institutions & Instruments, forthcoming.* https://doi.org/10.1111/fmii.12170

218

Brockman, P., & Unlu, E. (2009). Dividend policy, creditor rights, and the agency costs of debt. *Journal of Financial Economics, 92*(2), 276–299. https://doi.org/10.1016/j.jfineco.2008.03.007

Bureau of Economic Analysis. (2021). *Gross domestic product by state and personal income by state, 2nd quarter 2022*. https://www.bea.gov/data/gdp/gdp-state

Byrne, J., & O'Connor, T. (2012). Creditor rights and the outcome model of dividends. *The Quarterly Review of Economics and Finance, 52*(2), 227–242. https://doi.org/10.1016/j.qref.2012.04.002

Cho, S. S., El Ghoul, S., Guedhami, O., & Suh, J. (2014). Creditor rights and capital structure: Evidence from international data. *Journal of Corporate Finance, 25*, 40–60. https://doi.org/10.1016/j.jcorpfin.2013.10.007

DBRS Morningstar. (2022). *Methodology rating U.S. structured finance transactions*. https://www.dbrsmorningstar.com/research/394847/rating-us-structured-finance-transactions

Demiroglu, C., Dudley, E., & James, C. M. (2014). State foreclosure laws and the incidence of mortgage default, *The Journal of Law and Economics 57*(1), 255-280. https://doi.org/10.1086/674868

Djankov, S., Mcliesh, C., & Shleifer, A. (2007). Private credit in 129 countries. *Journal of Financial Economics*, *84*(2), 299–329. https://doi.org/10.1016/j.jfineco.2006.03.004

Esty, B. C., & Megginson, W. L. (2003). Creditor rights, enforcement, and debt ownership structure: Evidence from the global syndicated loan market. *The Journal of Financial and Quantitative Analysis*, *38*(1), 37. https://doi.org/10.2307/4126763

Fabozzi, F. J., Breemen, V. van, Vink, D., Nawas, M., & Gengos, A. (2022). How much do investors rely on credit ratings: Empirical evidence from the U.S. and E.U. CLO primary market. *Journal of Financial Services Research, 2022* https://doi.org/10.1007/s10693-021-00372-x

Fabozzi, F. J., & Vink, D. (2010). Looking beyond credit ratings: Factors investors consider in pricing European asset-backed securities. *European Financial Management*, *18*(4), 515–542. https://doi.org/10.1111/j.1468-036X.2010.00577.x

Fitch Ratings. (2020). *U.S. RMBS rating criteria*. https://www.fitchratings.com/research/structured-finance/us-rmbs-rating-criteria-11-05-2020

Furfine, C. H. (2014). Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies, 2*(2), 154–187. https://doi.org/10.1093/rcfs/cft008

Flynn, S., & Ghent, A. (2018). Competition and credit ratings after the fall. *Management Science*, *64*(4), 1477–1973. https://doi.org/10.1287/mnsc.2016.2604

Ghent, A. (2014). How do case law and statute differ? Lessons from the evolution of mortgage law. *The Journal of Law and Economics, 57*(4), 1085–1122. https://doi.org/10.1086/680931

Griffin, J. M., Nickerson, J., & Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *Review of Financial Studies*, *26*(9), 2270–2310. https://doi.org/10.1093/rfs/hht036

Gu, X., Kadiyala, P., & Mahaney-Walter, X. W. (2018). How creditor rights affect the issuance of public debt: The role of credit ratings. *Journal of Financial Stability, 39*, 133–143. https://doi.org/10.1016/j.jfs.2018.11.001

He, J. J., Qian, J. Q. J., & Strahan, P. E. (2015). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067

Houston, J. F., Lin, C., Lin, P., & Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics*, *96*(3), 485–512. https://doi.org/10.1016/j.jfineco.2010.02.008

Jayaraman, S., & Thakor, A. V. (2013). *The effect of creditor rights on bank monitoring, capital structure and risk-taking* [Working paper]. *Wells Fargo Advisors Center for Finance and Accounting Research Working Paper No. 13/003.* https://doi.org/10.2139/ssrn.2307676

Jiang, J. X., Wang I. Y., & Wang, K. P. (2018). Revolving rating analysts and ratings of MBS and ABS: Evidence from LinkedIn. *Management Science, 64*, 5461-5959*. https://doi.org/10.1287/mnsc.2017.2921*

Kroll Bond Rating Agency. (2021). *U.S. RMBS rating methodology*. https://www.kbra.com/documents/report/56/rmbs-u-s-rmbs-rating-methodology

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1997). Legal determinants of external finance. *The Journal of Finance*, *52*(3), 1131–1150. https://doi.org/10.2307/2329518

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, *106*(6), 1113–1155. https://doi.org/10.1086/250042

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (2000). Investor protection and corporate governance. *Journal of Financial Economics*, *58*(1–2), 3–27. https://doi.org/10.1016/S0304-405X(00)00065-9

Laura, M. R., & Fahad, N. (2017). Complexity in structured finance and difficulties faced by market participants - A critical assessment of the role of the complexity in financial crisis. *Asian Economic and Financial Review*, *7*(9), 907–920. https://ssrn.com/abstract=2998038

Mansi, S. A., Maxwell, W. F., & Wald, J. K. (2009). Creditor protection laws and the cost of debt. *The Journal of Law & Economic 52*(4), 701-717. https://doi.org/10.1086/605566

Miller, D. P., & Reisel, N. (2011). Do country-level investor protections affect security-level contract design? Evidence from foreign bond covenants. *Review of Financial Studies*, *25*(2), 408–438. https://doi.org/10.1093/rfs/hhr097

Moody's Investors Service. (2022). *Moody's approach to rating US RMBS*. Moodys. https://www.moodys.com/research/List-of-Rating-Methodologies--PBC_127479

National Credit Union Administration. (2020). *Non-agency RMBS concentration by state*. https://www.ncua.gov/support-services/guaranteed-notes-program/state-concentration-history

Qian, J., & Strahan, P. E. (2007). How laws and institutions shape financial contracts: The case of bank loans. *The Journal of Finance*, *62*(6), 2803–2834. https://doi.org/10.1111/j.1540-6261.2007.01293.x

Securities and Exchange Commission. (2012). *Annual report on nationally recognized statistical rating organizations.* https://www.sec.gov/files/nrsroannrep1212.pdf

Securities and Exchange Commission. (2014). *Asset-backed securities*. https://www.sec.gov/spotlight/dodd-frank/assetbackedsecurities.shtml

Securities and Exchange Commission. (2019). *What we do - The laws that govern the securities industry*. https://www.sec.gov/about/what-we-do

Securities and Exchange Commission. (2020). *Annual report on nationally recognized statistical rating organizations.* https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf

S&P Global Ratings. (2021). *RMBS: Methodology and assumptions for rating U.S. RBMS issued 2009 and later.* https://disclosure.spglobal.com/ratings/en/regulatory/article/-/view/sourceId/10426033

United States Census Bureau. (2020). *Average sales price of new manufacture homes sold or intended for sale by size of home by state* [Data set]. https://www.census.gov/data/datasets.html

Vink, D., Nawas, M., & van Breemen, V. (2021). Security design and credit rating risk in the CLO market. *Journal of International Financial Markets, Institutions and Money*, *72*, 101305. https://doi.org/10.1016/j.intfin.2021.101305

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817. https://doi.org/10.2307/1912934

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Chapter 6

Risk Retention in the European Securitization Market: Skimmed by the Skin-in-the-Game Methods?

Vivian M. van Breemen
Claudia Schwarz
Dennis Vink

Acknowledgement: *We thank Linda Goldberg (Federal Reserve Bank of New York), Patricia Mosser (Columbia SIPA), Loriana Pelizzon (Leibniz Institute for Financial Research SAFE) and Raphael Schoenle (Brandeis university and CEBRA) for their invitation to present our paper during the Central Bank Research Association (CEBRA) Annual Meeting 2023. We are very grateful for comments from Klaus Düllmann (ECB) on a previous version of the paper. We also benefited from comments provided by participants in the ECB Research Seminar. We also thank the Editorial Board of the European Central Bank (ECB) Working Paper Series for their review and invitation to publish in the ECB Working Paper Series*

Abstract

We empirically investigate the impact of the regulatory risk retention methods on the credit ratings and pricing at issuance using a sample of European securitization tranches issued in the period 2011-2021. European regulation treats all risk retention methods equally. We show that credit ratings differ for securitization tranches of different risk retention methods. We also find that credit rating agencies experience more rating disagreements depending on the risk retention method. Finally, when we investigate the impact of these methods on the pricing of securitization tranches, our results show that investors adjust the risk premium accordingly. Our findings strongly suggest reevaluating the different regulatory risk retention methods.

Keywords: risk retention rule, primary issuance spread, credit ratings.

JEL classifications: G12, G21, G24, G28.

6.1 Introduction

In a securitization transaction, unlike in traditional lending where the lender owns and service the loans they originate, the ownership and risk of the loans are (partially) transferred to investors. Using this method, a potential conflict of interest might arise when the loan originators have not enough *skin-in-the-game*, meaning, the vast majority (or all) of the risks are transferred to investors while the originator is barely exposed to any risk. If the originators have little *skin-in-the-game*, they might have lower incentives to carefully assess and monitor the risks of the mortgages that they originate with the sole purpose to securitize. In fact, critics argue that the cause, and intensity of, the Global Financial Crisis (GFC) that began in 2007 is a direct result of a decline in originators' screening standards and lack of sufficient portfolio management that was fostered by the originate-to-distribute model of securitization.

An extensive body of literature indeed shows the relationship between default rates and whether or not a mortgage was securitized (see, e.g., Demiroglu & James, 2015; Demyanyk & Van Hemert, 2009; Keys et al., 2010). In response to the significant impact of the securitization market on the GFC, regulators have implemented several rules and regulations for securitization transactions.[66] Regarding the screening and monitoring incentives of originators, securitization regulation in the European Union[67] (the Securitization Regulation hereafter) has sought to improve the *skin-in-the-game* of the originators of securities via the risk retention rule. In addition, securitizations compliant with the criteria for simple, transparent and standardized securitizations (STS hereafter) can benefit from preferential capital treatments. The risk retention rule, that entered

[66] See, e.g., Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on CRAs.

[67] Regulation (EU) No 2017/2402 of the European Parliament and of the Council of 12 December 2017 laying down a general framework for securitization and creating a specific framework for simple, transparent and standardized securitization, and amending Directives 2009/65/EC, 2009/138/EC and 2011/61/EU and Regulations (EC) No 1060/2009 and (EU) No 648/2012.

into force as of 2011 for new securitizations, are set out in Article 405 of the Capital Requirements Regulation (CRR)[68] for securitizations issued before 2019 and securitizations issued thereafter should comply with the Securitization Regulation. The rules state that the originator, sponsor, or original lender should, at all times, retain a material net economic interest of no less than 5% in the securitization transaction. The purpose of the rule is to better align the interest of the originator and investor by requiring the originator to retain a significant portion of so-called *skin-in-the-game*.

The rule allows the originator to select one of the different regulatory risk retention methods to hold their portion of *skin-in-the-game*. A portion of the equity tranche, corresponding to at least 5% of the total nominal value of the securitized exposures, is retained in the first loss tranche (FLT) method and in the first loss exposure (FLE) method at least 5% of the credit risk at the level of every securitized exposure is retained. While in the vertical slice (VES) method, the retainer retains a portion of each tranche of minimum 5%. In the on-balance sheet (OBS) method, the retainer keeps a randomly selected portion of the exposures of at least 5% of the nominal value from the envisaged asset pool in his books.

The starting point of our study is that the European risk retention rules do not distinguish between the different risk retention methods and allows the originator to use whatever option suits best, without any consequences on the capital relief. This seems surprising, given that these methods differ in terms of risk and return profiles for both the retainer and the investor and the way their incentives align. In line with that, previous literature (see, e.g., Bektić & Hachenberg, 2021; Kiff & Kisser, 2014; Malekan & Dionne, 2014) provides evidence for existing differences. As the different risk retention methods vary in terms of risk profile, we would expect that these methods have an impact on

[68] Article 405 of Regulation (EU) No 575/2013 Retained interest of the issuer.

the credit rating and pricing of securitization tranches at issuance. We seek to investigate this along several dimensions. First, we test whether the different risk retention methods have an impact on the credit rating at issuance. Second, we analyze if the different risk retention methods have caused credit rating agencies (CRAs) to report split ratings. Third and finally, we investigate if investors take into account the risk retention method in pricing the tranche beyond the credit rating at the time of issuance.

Using a unique dataset of European securitization transactions that are issued and sold between 2011 and 2021, we provide the following results. *First*, we show that CRAs assign worse ratings, on average, for tranches that have the VES method, compared to the base method FLT. However, as data limitations hinder to control for inherent risk of the underlying pool, we cannot rule out that securitizations with the VES method have on average riskier assets. *Second*, we find that CRAs experience more rating disagreements when rating securitizations with the FLT method. When comparing the originator's size, we find less rating disagreement for tranches that are originated by infrequent originators. *Third*, our results show that investors differentiate between the different risk retention methods when pricing securitization tranches at the time of issuance, even when controlling for the inherent risks as proxied by the rating. Taking the FLT method as the base case, we find that investors reduce the spread at issuance when the tranche retainer has applied the VES or OBS methods. We conclude that, rating agencies as well as markets seem to believe that the retention methods signal different incentives for adequately screening and monitoring securitized exposures and aligning interests of originators and investors.

The contribution of our study is manifold. First, to the best of our knowledge, we are the first to assess the impact of four different risk retention methods on the credit ratings and pricing of European securitization tranches. We thereby contribute to studies that examine the effectiveness of the risk retention rule (see, e.g., Agarwal et al., 2021; Chouliara & Martino, 2021), the very few studies that touch upon the form of risk retention (see, e.g., Bektić & Hachenberg, 2021; Malekan & Dionne, 2014), and on pricing of securitizations (e.g., Fabozzi et al., 2022). These studies show that differences in risk perception exist between the FLT and VES method. The salient feature of our study is that, unlike previous studies, we compare not only the FLT and VES method, but also the OBS and FLE method. In addition, we also analyze the impact on the credit rating and CRA disagreements. Second and more importantly, we provide striking insights for regulators and supervisors on the effectiveness of the current regulatory framework for securitization transactions.

The remainder of our paper is structured as follows. Section 6.2 reviews the related literature and regulation. Section 6.3 describes the data used and sets forth our empirical strategy. Section 6.4 describes the data observations and trends. Section 6.5 provides the empirical results and, finally, Section 6.6 concludes.

6.2 Risk retention and securitizations

6.2.1 **Regulatory risk retention methods**

Initiated by G20 leaders during the Pittsburgh Summit in September 2009, the securitization sponsors or originators should retain part of the credit risk of the underlying asset, with the purpose to ensure strong alignment of interest between the issuers and the investor of the securitization (EBA, 2014b). The International Organization of Securities (IOSCO) stretched a similar conclusion in their September 2009 report on 'Unregulated Financial Markets and Products' (IOSCO, 2009). They also recommended that it is highly important to tailor such retention requirements with great detail to make sure that the interests of all parties are properly aligned. The goal of such risk retention rules is to incentivize originators, issuers and investors to apply accurate quality screenings, improve underwriting standards and appropriately monitor the underlying credit risks (EBA, 2014b).

As a result, the risk retention rule was introduced for new securitizations in 2011. Article 405 of the Capital Requirements Regulation (CRR)[69] sets forth the risk retention rules for securitizations issued before 1 January 2019 and all securitizations issued thereafter should follow the Securitization Regulation.[70] The requirements relating to the risk retention pursuant to Article 6(7) of Regulation (EU) 2017/2402 are specified in the EBA final draft regulatory technical standards.[71] According to the rule, a material net economic interest of no less than 5% should be retained at all times by the tranche retainer. The retainer should officially document this and share the information with the investor. The regulation also prohibits the originator or the sponsor from directly or indirectly hedging or otherwise transferring the risks of the securitization. Also, it sets-out additional disclosure requirements to which the sponsors and originators need to comply, such as due diligence requirements. In applying the risk retention rule, the retainers should follow *one* of the five risk retention methods as set out by regulation. Hence, a combination of risk retention methods is not allowed, and one is also not allowed to change the method during the term of the transaction. *The CRR and Securitization Regulation allow the following five methods to be used as a risk retention method:*

1. ***Vertical Slice (VES)**: a retention of no less than 5% of the nominal value of each of the tranches sold or transferred to investors.*

[69] Article 405 of Regulation (EU) No 575/2013 Retained interest of the issuer.

[70] Regulation (EU) No 2017/2402 of the European Parliament and of the Council of 12 December 2017 laying down a general framework for securitization and creating a specific framework for simple, transparent and standardized securitization, and amending Directives 2009/65/EC, 2009/138/EC and 2011/61/EU and Regulations (EC) No 1060/2009 and (EU) No 648/2012.

[71] EBA final draft regulatory technical standards - Specifying the requirements for originators, sponsors, original lenders and servicers relating to risk retention pursuant to Article 6(7) of Regulation (EU) 2017/2402 as amended by Regulation (EU) 2021/557.

2. ***On-balance Sheet (OBS)****: a retention of randomly selected exposures equivalent to not less than 5% of the nominal value of the securitized exposures.*
3. ***First Loss Tranche (FLT)****: the retention of the equity tranche and, if necessary, other tranches that have the same or more severe risk profile than those transferred or sold to investors and are not maturing any earlier, so that the retention equals in total no less than 5 % of the nominal value of the securitized exposures.*
4. ***First Loss Exposure (FLE)****: the retention of the FLE of not less than 5% of every securitized exposure. It needs to be applied so that the credit risk retained is always subordinated to the credit risk that has been securitized in relation to those same exposures. The retention may also be fulfilled by the sale of the tranches at a discounted value of the underlying exposures of not less than 5%.*
5. ***Pari Passu Share/ Revolving Exposure****: a retention of the originator's interest of not less than 5% of the nominal value of each of the securitized exposure.*[72]

In the OBS method, the retainer keeps a portion of the underlying pool of residential mortgages backing the securitization transaction, which is randomly selected.[73] In the VES and FLT methods, the retainer holds part of the risk using the securitization structure. The securitization structure is created by different layers of tranches that each have its own risk profile. In the FLT method, the (first) tranche with the highest risk profile (non-investment grade) is retained, while in the VES method, a small portion of all tranches in the deal are retained. The FLT is often referred to as the horizontal part, as the retainer literally holds a horizontal

[72] We do not focus on this method in our study because the revolving securitization is mostly applicable to revolving master trust structures, and the number of transactions is too low for statistical analysis.

[73] The selection procedure needs to ensure that the exposures retained are random by for example including appropriate quantitative and qualitative factors such as vintage, product, geography, origination date, maturity date, property type, industry sector, and outstanding loan balance.

slice of the transaction while in the VES the upright portion is retained, referred to as the vertical part.

EBA (2014b) explored the possibility of adding a sixth retention method that allows a combination of the VES method and the FLT method, a so called 'L-shape' form of retention. However, they have concluded that, apart from those five forms of risk retention already available, no other form should be considered. The current methods are deemed sufficient and by providing more options it might well be that the chosen form is not as effective in aligning interest and reduce risks. EBA also concluded that the 'L-shape' retention option explored would add to the complexity of measuring the net economic interest. In the United States, an L-shape form of retention is allowed by regulation.

6.2.2 **Related literature**

Since the introduction of the risk retention rule, a still rather scarce but growing body of literature has been created. Interestingly, the empirical evidence is rather mixed. On the one hand, literature (e.g., Vanasco, 2017) provides evidence that the FLT method is best aligning the interests between the tranche retainer and investor. For example, Kiff and Kisser (2014) and Malekan and Dionne (2014) argue that the VES method, compared to the FLT, is not optimal for aligning the incentive between the originator and investors. These studies are in favor of the FLT method and argue that this method creates better screening and monitoring efforts by the retainer. Likewise, Hibbeln and Osterkamp (2020) find that investors demand a significantly lower portion of risk premium when the FLT methods is used, compared to the VES method.

On the other hand, Bektić and Hachenberg (2021) for example, hypothesize that with the FLT (horizontal) method, the interest of the originator and investor are not necessarily aligned. In the FLT method, the tranche retainer bears (part of the) risk of the first loss tranche. They argue, however, that besides the subordinated performance fee, the tranche retainer also benefits from excess cash flow in the securitization. This might create an incentive for the tranche retainer to buy riskier collateral to optimize its own profits. However, they find no significant results between the retention methods (horizontal vs. vertical) and collateralized loan obligations (CLO) spreads. In line with Bektić and Hachenberg, Tavakoli (2008) also sees a clear conflict of interest when the originator retains the equity cash flows. She explains that there is a risk of moral hazard; the manager gains from high spread income of the portfolio when the losses exceed the initial equity investment of the manager. Besides, the equity owner has the power to refinance and call the transaction when spreads are tightening. Kaptan (2011) argues that an optimal alignment between retainer and investor can only be achieved when introducing an incentive-maximizing retention structure. He suggests that higher default rates should correspond with higher risk retention, as this will incentivize tranche retainers to have better screening and monitoring efforts.

To summarize, the regulatory risk retention rule does not distinguish between the different risk retention methods. However, empirical evidence in literature shows that differences do exist between the risk profile of the various risk retention methods. Nevertheless, the findings of previous studies are rather mixed. Some find that the FLT method is best aligning the interest of the retainer and investor, while others argue that the VES method is more suitable in aligning interests.

6.2.3 **Risk retention and incentives alignment**

The purpose of the risk retention rule is defined as follows:

> "*The purpose of the requirement to retain a material net economic interest is to align the interests between two sets of parties in a securitisation: the sell-side*

parties that transfer the credit risk of the securitised exposures, and the investors that assume or purchase the credit risk." – EBA (2022)

However, one might argue that the incentive to monitor and manage the loan book is different for the various risk retention methods. We explore this by theoretical considerations and simulated the return per loss rate of both the retained part and the part sold to investors (see Appendix I for an example). Per construction, the risk profile for the retainer and investor is mathematically identical for the VES method, as the retainer holds a portion of each tranche in the securitization (see Figure I(a), Appendix I). If we assume that the pool is sufficiently diversified and the retention part was truly randomly selected in the OBS method, one might argue that this method would lead to similar loss rates and thus similar returns for the two market participants. Our example confirms these considerations (see Figure I(b), Appendix I)[74]. In the FLE method, the tranche retainer sells the tranche at a discount. Due to the waterfall payment structure of securitizations, this means that the return function for the retainer exhibits kinks. The very first losses up until 5% of the equity tranche are solely borne by the retainer, and the subsequent losses are incurred by the investor up until the equity tranche is 'eaten up'. If losses exceed the size of the equity tranche, the subsequent losses are borne again solely by the retainer up until 5% of the next tranche, and so on. Thus, the return profiles of the retainer and investor differ substantially (see Figure I(c), Appendix I for an example). In the FLT method, the retainer holds 5% of the securitization in the equity tranche. If the equity tranche is larger than 5% of the total securitization, the first losses are shared between the retainer and investor, given that they rank pari passu. However, as the retainer only holds part of the equity tranche, his returns are 'eaten up' rather quickly when losses occur. If losses exceed the equity tranche, the retainer has lost 100% of the value of his retention amount, while losses for the investor are still rather limited (see

[74] Minor differences may arise due to the difference between the coupons paid on the tranches versus the interest income received.

Figure I(d), Appendix I). This suggests that the retainer takes the bulk of the first losses, but has no incentive to monitor and manage the loan pool (e.g., manage arrears, forbearances, foreclosures, seizure of assets) in an optimal manner once the retainer assumes that total losses will anyway exceed the size of the equity tranche.

In sum, considering the expected returns, incentives alignment between retainer and investor is perfect for VES, closely aligned for OBS, rather divergent for FLE and very divergent for FLT. Yet, as the retainer takes the first losses, the incentives to securitize junk may be limited and thus the FLT could also be seen as a signal of confidence in the quality of the pool of the retainer to the market.

This argumentation as well as previous literature has led us to empirically scrutinize if the different risk retention methods indeed align the interest between the two sets of parties in a securitization in an equal manner. We argue that the different risk retention methods allowed by regulation do not contribute to identical risk profiles and incentives and, as a result, are likely to impact the credit rating and pricing of securitization tranches at issuance. Hence, we expect to find significant differences in credit ratings and pricing for tranches with different risk retention methods.

6.3 Sample construction and empirical strategy

The primary data source for this study is *Bloomberg*. From *Bloomberg*, we obtained the complete universe of 5,234 securitization tranches that are issued and sold in the European Union between 2011 and 2021. The cut-off date is 2011 as this is the year in which the rule came into force. In order to avoid problems with possible misclassification of deals, we have eliminated tranches with missing credit rating information (1,142 tranches), incomplete deals (8 tranches), and those without information on the risk retention method (1,927 tranches). Finally, the remaining 2,157 tranches (41%) with a total value of €957 billion, present our *full tranche-level sample*. An overview of all the variables and their definitions is provided in Table 6.1 and the summary statistics of our variables are given in Table 6.2.

A securitization is an investment product that is backed by a pool of assets and, naturally, the securitization is relying on the performance of these assets. The underlying collateral of the asset pool can vary in type, for example, corporate loans, mortgage loans or student loans. In our study, we have included the full scope of securitization types, ranging from asset-backed securities (ABS), residential mortgage-backed securities (RMBS), commercial mortgage-backed securities (CMBS) to CLOs. The majority of tranches in our sample are ABS (45.48%), followed by RMBS (39.45%), CMBS (7.56%) and CLO (7.51%), see Panel C of Table 6.2. In our sample, 48.45% of the tranches use the FLT method and 34.08% the VES method. The OBS method is used in 14.97% of the cases and only in a few cases (2.50%) the FLE method is used (see Figure 6.1 and Panel B of Table 6.2). We are also interested in the size of the originator as a larger originator might be more powerful and knowledgeable than the smaller ones. The slight majority of our sample (54.29%) is originated by an originator that is amongst the top 10% largest (in terms of number of tranches). The remaining tranches (45.71%) are originated by the non-top 10% originators, see Figure 6.2 and Panel D of Table 6.2.

The tranches in our sample received at least one credit rating of Moody's, S&P, Fitch, DBRS or KBRA. In our sample, we observe a similar portion of tranches rated by DBRS (32.80%), Moody's (28.01%), S&P (20.27%) and Fitch (17.62%). While a negligible number of tranches (1.30%) are rated by KBRA, see Panel E of Table 6.2. The majority of tranches (77.61%) in our sample received two credit ratings at issuance, see Panel G of Table 6.2. Only 13.54% received one credit rating, three credit ratings were assigned to just 8.39% of tranches and a small portion of tranches (0.46%) received four credit ratings at issuance. Of the tranches that received more than one credit rating, the majority received credit ratings that are the same (47.29%), see Panel F of Table 6.2. For the remaining tranches we observe rating discrepancy; 25.20% of the tranches in our sample received a rating at issuance with one notch difference, 14.62% with two notches, 6.77% with three notches, and 6.14% more than three notches difference. Finally, we are interested in the primary issuance spread as this represents the risk premium demanded by investors for securitization tranches. The mean spread at issuance is highest for the VES method (170.63 bp), followed by the FLT method (152.1 bps) and OBS method (134.4). For the FLE method we observe a relative low mean spread at issuance (104.1 bps), see Panel H of Table 6.2.

Table 6.1: Brief description of all variables.

Variable	Description	Source
Spread	Spread at the date of issuance of the respective securitization tranche, noted in basis points above its benchmark.	*Bloomberg*
Rating Discrepancy	Notches difference that results from calculating the numerical difference in credit rating of Moody's, S&P, Fitch, DBRS and KBRA, in case the tranche received multiple ratings.	*Own calculations*
Risk Retention Methods	The method to determine the 5% material net economic interest, which includes the *VES*, *OBS*, *FLT* or *FLE* method.	*Bloomberg*
Subordination Level	Level of internal credit enhancement supporting the security within a securitization, measured as the ratio of all tranches subordinated to the tranche in question divided by the total face value of the securitization.	*Own calculations*
No. of Tranches	Total number of tranches in the securitization of which the security is part of.	*Bloomberg*
Log Tranche Value	The natural logarithm of the tranche value at issuance, measured in Euro.	*Bloomberg*
Log Transaction Value	The natural logarithm of the transaction value of the deal at issuance, measured in Euro.	*Bloomberg*
Benchmark Rate	The market wide benchmark type used for the security at issuance (i.e., EURIBOR 3-months).	*Bloomberg*
Frequent Originator	A dummy that equals 1 if the tranche's originator is among the top 10% largest originators, measured by number of tranches contributed to the total number of securities issued in the EU (2011-2021), and 0 otherwise.	*Own calculations*
STS Compliant	A dummy that equals 1 if the securitization is compliant with the STS criteria at the time of issuance, and 0 otherwise.	*Bloomberg*
Single Originator	A dummy indicating 1 if the deal is originated by a single originator, and 0 if the deal is originated by multiple originators.	*Bloomberg*
GDP Growth Rate	The annual percentage growth rate of GDP in the country to which the risks of the securitization are exposed to.	*European Central Bank*
Credit Rating	Average credit rating of Moody's, S&P, Fitch, DBRS, and KBRA converted into a numerical value by setting 1 for Aaa, 2 for Aa1, 3 for Aa2, and so on.	*Bloomberg*
Security Type	Indicates the type of underlying assets of the securitization of which the security is part, ranging from ABS, RMBS, CMBS, to CLOs.	*Bloomberg*
Year	Date at which the security is issued.	*Bloomberg*
Country of Risk	The country to which the (majority of the) securitization's risks are exposed to.	*Bloomberg*

Table 6.2: Summary statistics.

This table reports summary statistics of securitization tranches issued from 2011 to 2021. 'Rating Discrepancy' represents the notches difference that results from calculating the numerical difference in credit rating of Moody's, S&P, Fitch, DBRS and KBRA. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. 'Subordination Level' represents the level of internal credit enhancement supporting the security within a securitization, measured as the ratio of all tranches subordinated to the tranche in question divided by the total value of the securitization. 'No. of Tranches' is the total number of tranches in the securitization of which the security is part of. 'Log Tranche Value' is the natural logarithm of the tranche value at issuance, measured in Euro. 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance, measured in Euro. 'Frequent Originator' is a dummy that equals 1 if the tranche's originator is among the top 10% measured by number of tranches contributed to the total number of securities issued in the EU (2011-2021), and 0 otherwise. 'Credit Rating' represents the average credit rating provided by Moody's, S&P, Fitch, DBRS and KBRA. We have converted the ratings into a numerical value by setting 1 for Aaa, 2 for Aa2, 3 for Aa2, and so on. 'Security Type' represents the type of securitization of which the tranche is part of, ranging from ABS, RMBS, CMBS, to CLOs. 'Year' represents the year in which the security is issued. 'Spread' is the quoted margin between the benchmark rate and the coupon of the initial spread, in basis points. 'Benchmark Rate' is the market wide benchmark type used for the security at issuance.

Panel A: Overall Summary Statistics

Variable	N	Mean	Median	Std	P25	P75
Rating Discrepancy	2157	0.91	0.00	1.34	0.00	1.00
Risk Retention Methods	2157	2.19	3.00	0.94	1.00	3.00
Subordination Level (in %)	2157	0.26	0.15	0.28	0.06	0.34
No. of Tranches	2157	5.31	5.00	2.80	3.00	7.00
Tranche Value (in mio)	2157	444	70,8	1150	20	440
Log Tranche Value	2157	18.32	18.10	1.86	16.81	19.90
Tranche Value (in mio)	2157	1110	629	1720	361	1070
Log Transaction Value	2157	20.32	20.26	0.95	19.71	20.80
Frequent Originator	2157	0.54	1.00	0.50	0.00	1.00
Credit Rating	2157	5.92	5.00	4.57	2.00	9.00
Security Type	2157	2.10	2.00	1.07	1.00	3.00
Year	2157	2018.01	2018	2.28	2016	2020
Spread (in bps)	354	153.51	117.5	124.67	65	200
Benchmark rate	354	3.77	4.00	0.48	3.00	4.00

Panel B: Risk Retention Methods

	Freq.	Percent
FLT	1045	48.45
VES	735	34.08
OBS	323	14.97
FLE	54	2.50
Total	2157	100

Panel C: Security Type

	Freq.	Percent
ABS	981	45.48
RMBS	851	39.45
CMBS	163	7.56
CLO	162	7.51
Total	2157	100

Panel D: Risk Retention Methods sorted by (in)frequent originator (no. of tranches)

	FLT	*VES*	*OBS*	*FLE*	*Total*
Frequent Originator	500	427	213	31	1171
Infrequent Originator	545	308	110	23	986
Total	1045	735	323	54	2157

Panel E: Credit Rating Agencies

	Freq.	Percent
Moody's	1183	28.01
S&P	856	20.27
Fitch	744	17.62
DBRS	1385	32.80
KBRA	55	1.30
Total	4223	100

Panel F: Rating Discrepancy *(multiple-rated tranches only)*

Rating notches difference		Freq.	Percent
	0	880	47.29
	1	469	25.20
	2	272	14.62
	3	126	6.77
	4	69	3.71
	5	23	1.24
	6	13	0.70
	7	7	0.38
	8	2	0.11
Total		1861	100

Panel G: Number of Ratings

	Freq.	Percent
1	292	13.54
2	1674	77.61
3	181	8.39
4	10	0.46
	2157	100

Panel H: Spread at issuance (in bps)

	VES	*OBS*	*FLT*	*FLE*	*Total*
Mean Spread (in bps)	170.63	134.4	152.1	104.1	153.51
Observations	108	52	182	12	354

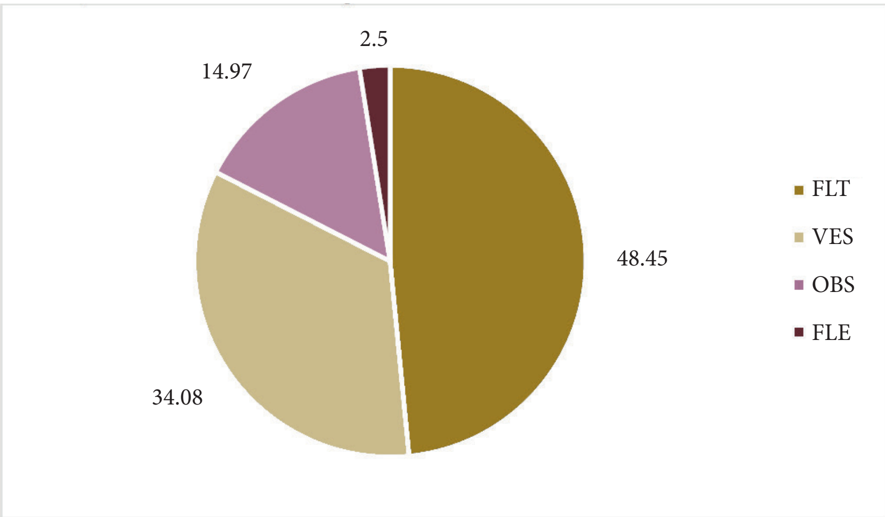


Figure 6.1: Risk retention methods (% of total sample).

This figure illustrates the percentage of tranches in our final sample with the FLT, VES, OBS, and FLE method. 'VES' stands for vertical slice, 'OBS' for on-balance sheet, 'FLT' for first loss tranche, and 'FLE' for first loss exposure.

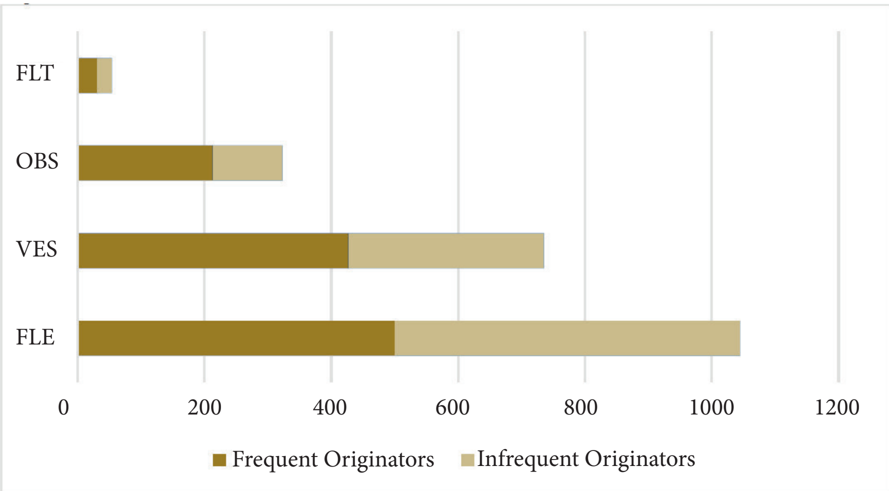


Figure 6.2: Risk retention methods sorted by frequent vs. infrequent originator (no. of tranches).

This figure illustrates the number of tranches in our final sample that are originated by frequent and infrequent originators, for each of risk retention methods. 'VES' stands for vertical slice, 'OBS' for on-balance sheet, 'FLT' for first loss tranche, and 'FLE' for first loss exposure.

6.3.1 **Strategy for data observations and trends**

The risk retention rule came into force as of 2011 but it took some time for issuers to find a way to comply with the rule, therefore data on risk retention methods available in *Bloomberg* before 2014 is scarce. To describe data trends, we have discarded the limited number of observations before 2014. In Figure 6.3(a), we display the total issuance volumes and the number of deals in our sample. Interestingly, we observe a significant increase in the number of newly issued securitizations from 2017 onwards. However, issuance volumes have relatively stable trend. Perhaps, with the introduction of the Securitization regulation in 2017, the confidence in the securitization market has slightly grown with rising issuance volumes as a result. In Figure 6.3(b), we display the number of deals over time sorted by risk retention method. We observe a relatively stable trend for FLT, OBS and FLE in the period 2014-2021. While interestingly, we observe a significant increase in tranches with the VES method after 2017[75.]

To explore this trend empirically we apply logit regressions. We use deal-level data and limit our sample to deals with the FLT and VES method only. As we are trying to understand what influences the issuer's choice, we use a number of control variables. Starting with the motive for originators, as explained later in section 6.4.1, there are several motives for securitizing a pool of assets, among which capital relief is a prominent one and this is typically linked to the VES method. Thus, we analyze if deals that are STS compliant are more likely to have the VES method. '*STS Compliant*' is a dummy that equals 1 if the deal is compliant with STS criteria at the time of issuance, and 0 otherwise. To analyze whether time effects or macroeconomic conditions influence the risk retention choice, we include the year in which the securitization was issued, the '*Country of Risk*' and the '*GDP Growth Rate*' (the annual percentage growth rate of GDP in the country to which the assets of the securitization are mainly exposed to).

[75] In Figure 6.1, we display the data without other filters, but a similar trend is observed if we use our final sample.

We also assess whether specific attributes of the originator influence the choice for a particular risk retention method. One attribute is the originator's size or "experience" in securitizing, which is proxied by *'Frequent Originator'.* This is a manually calculated dummy variable indicating one if the tranche's originator is amongst the top 10% largest originators, measured by number of tranches in the total number of securities issued in the EU (2011-2021), and zero otherwise. In addition, we include the variable '*Single Originator*', a dummy that is 1 if the deal is originated by a single originator, and 0 if the deal is originated by more than one originator. Furthermore, we test attributes of the deals, namely '*No. of Tranches*', the total number of tranches in the securitization of which the security is part of, and *Security Type*, the different types of underlying assets in the securitization, ranging from ABS, RMBS, CMBS, to CLO. '*Credit Rating*' is a proxy for the riskiness of the underlying assets and represents the average credit rating provided by Moody's, S&P, Fitch, DBRS and KBRA. We have converted the ratings into a numerical value by setting 1 for Aaa, 2 for Aa2, 3 for Aa2, and so on.[76] The specification of our first model is:

$$\begin{aligned} FLT\ vs.VES_{i(t)} = \beta_0 + \ & \beta_1 STS\ Compliant_{i(t)} \\ & + \beta_2 Country\ of\ Risk_{i(t)} + \beta_3 GDP\ Growth\ Rate_{i(t)} \\ & + \beta_4 Frequent\ Originator_{i(t)} \\ & + \beta_5\, Single\ Originator_{i(t)} + \beta_6\, No.of\ Tranches_{i(t)} \\ & + \beta_7\, Security\ Type_{i(t)} + \beta_8\, Credit\ Rating_{i(t)}\ \varepsilon_{i(t)} \end{aligned} \tag{6.1}$$

where ϵ_{ijt} is the idiosyncratic error term. The data vary by year *(t)* and deal *(i).*

Next, to further observe trends in our data, we investigate whether the security design characteristics are the same for securitization tranches with different risk retention methods. We do so by applying t-tests, using our *full tranche-level*

---

[76] We use Moody's credit rating scale as an example, but we have converted the different credit rating scales of all CRAs in our sample (Moody's, S&P, Fitch, DBRS and KBRA).

sample, to assess if significant differences exist between the security design characteristics of tranches with the VES, OBS, FLE methods compared to the FLT method. We use *No. of Tranches*, *Tranche Size*, *Transactions Size* and *Subordination level* as our security-design characteristics. *Tranche Value* and *Transaction Value* are the tranche and transaction value at issuance, measured in euros. These characteristics are important to capture the underlying risks of the securitization. As larger deals, with more underlying tranches and higher amount of underlying loans, make it more challenging and difficult to capture potential risks and returns (see, e.g., Furfine, 2014). Finally, we include *Subordination Level*, representing the percent of protection from losses for each tranche in the capital structure. As this measure is not readily available in *Bloomberg,* we manually calculate the ratio of all tranches subordinated to the tranche in question divided by the total face value of the deal. This measure indicates the precent of cushioning in the capital structure of a securitization deal, against credit losses that a specific tranche could suffer (see, e.g., Vink et al., 2021). The specification of our second model is:

$$t = \frac{(\bar{x}_{FLT} - \bar{x}_{other\ (VES,OBS,FLE)})}{\sqrt{\frac{s^2_{FLT}}{n_{FLT}} + \frac{s^2_{other(VES,OBS,FLE)}}{n_{other(VES,OBS,FLE)}}}} \tag{6.2}$$

where x̄ is the observed mean of the sample, s the standard deviation of the sample, and n the size of the sample.

Figure 6.3(a) Total issuance volumes (bln) and number of deals per year.

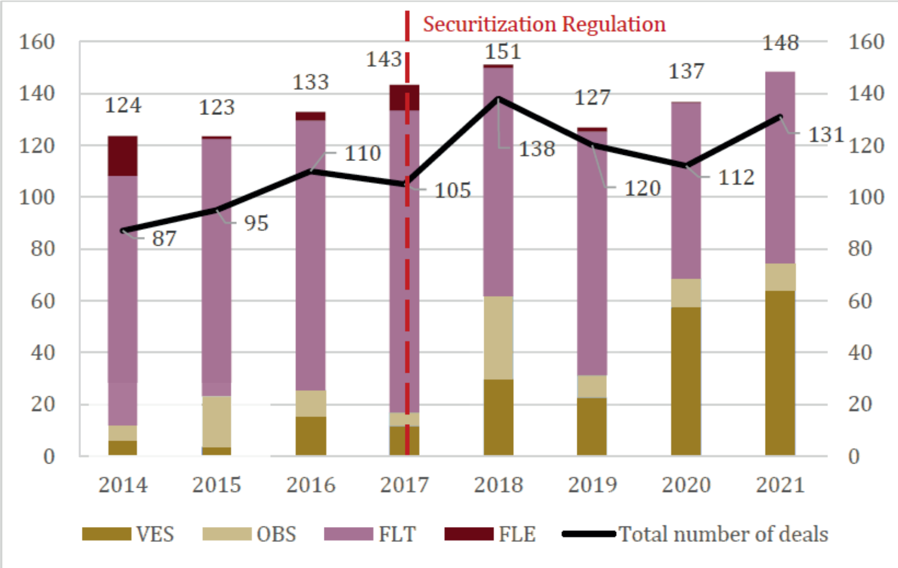


Figure 6.3(b) Number of deals sorted by risk retention methods and year.

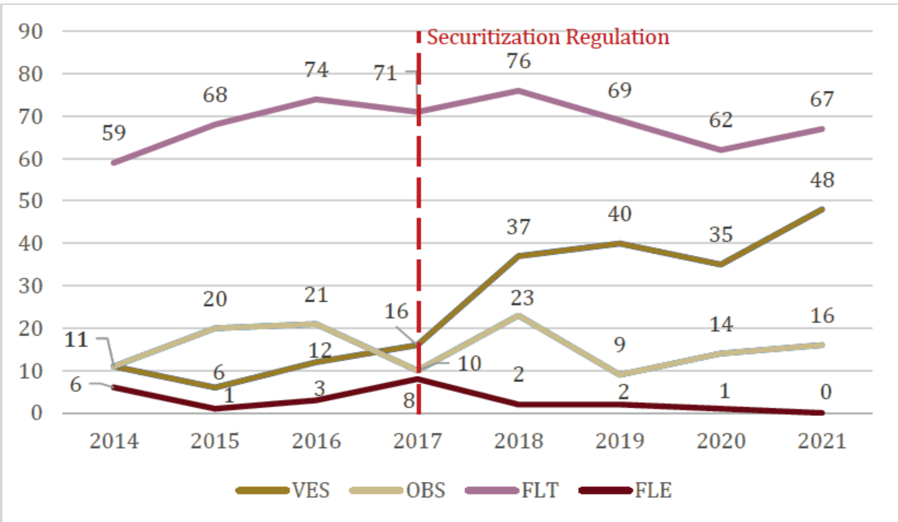


Figure 6.3: Risk retention methods over time.

This figure illustrates the number of deals that are issued between 2014 and 2021. Figure 6.3(a) illustrates the volume and number of deals over time in our dataset for deals with available information on the risk retention method. Figure 6.3(b) illustrates the number of deals over time sorted by risk retention method. 'VES' stands for vertical slice, 'OBS' for on-balance sheet, 'FLT' for first loss tranche, and 'FLE' for first loss exposure.

6.3.2 **Strategy for obtaining the empirical results**

We use three empirical strategies to investigate the impact of the different risk retention methods on the credit ratings and pricing of securitization tranches at the time of issuance. First, we analyze the impact of the different risk retention methods on the credit ratings at issuance. Using our *full tranche-level sample*, we apply ordered logit regressions with the *Credit Rating* as the dependent variable. We calculate the average credit rating received by Moody's, S&P, Fitch, DBRS, and KBRA for the tranche at time of issuance. Our key independent variable is *Risk Retention Methods*, a categorical variable denoting the four different risk retention methods in our sample, namely the *VES*, *OBS*, *FLT*, and *FLE* method. In addition, we use several variables to control for security-specific factors. We control for the security-design characteristics such as *No. of Tranches*, *Log Tranche Value*, *Log Transaction Value,* and *Subordination*. We also control for the size of the originator by including *Frequent Originator*. We further control for *Rating Discrepancy*, which stands for the numerical difference between credit ratings of different CRAs and exist only when the tranche is rated unequally by CRAs. We measure rating discrepancy as the numerical difference in notches that results from subtracting a numerical equivalent of the highest credit ratings assigned at issue from the numerical equivalent of the lowest credit ratings assigned at issue. For example, the indicator is one, if Moody's assigns a one notch higher (e.g., AAA) rating than S&P (e.g., AA) for the same tranche. This indicator shows possible misalignments between credit risk assessments of different CRAs for the same tranche. Hence, a higher discrepancy might indicate higher uncertainty and thus higher risks for investors. Next, we control for the *Security Type* and *Year* in which the tranche was issued. Due to data limitations, we cannot control for inherent risk of the securitization pool. The specification of our third model is:

$$
\begin{aligned}
Credit\ Rating_{j(t)} \\
&= \beta_0 + \beta_1 Risk\ Retention\ Methods_{i(t)} \\
&+ \beta_2 Subordination\ Level_{j(t)} \\
&+ \beta_3 No.of\ Tranches_{i(t)} + \beta_4 Log\ Tranche\ Value_{j(t)} \\
&+ \beta_5\ Log\ Transaction\ Value_{i(t)} \\
&+ \beta_6\ Frequent\ Originator_{i(t)} \\
&+ \beta_7\ Rating\ Discrepancy_{j(t)} \\
&+ \ Year\ and\ Security\ Type\ Controls_{ij(t)} + \varepsilon_{ij(t)}
\end{aligned}
\tag{6.3}
$$

where ϵ_{ijt} is the idiosyncratic error term. The data vary by year *(t)*, deal *(i)* and security *(j)*.

Second, we use ordered logit regressions with *Rating Discrepancy* as the dependent variable to investigate if there is a disagreement between the credit rating of different CRAs (i.e., rating discrepancy). To observe rating discrepancy, we only include tranches that have received at least two credit ratings at issuance. By eliminating all single-rated tranches (292 tranches), we obtain our *multiple-rated subsample* that consists of 1,865 tranches. Our key independent variable is the categorical variable *Risk Retention Methods*. Consistent with our third model, we control for several security-design characteristics (*No. of Tranches*, *Log Tranche Value*, *Log Transaction Value* and *Subordination*), *Frequent Originator*, *Credit Rating*, *Year* and *Security Type.* The specification of our fourth model is:

$$
\begin{aligned}
Rating\ Discrepancy_{j(t)} \\
&= \beta_0 + \beta_1 Risk\ Retention\ Methods_{i(t)} \\
&+ \beta_2 Subordination\ Level_{j(t)} + \beta_3 No.of\ Tranches_{i(t)} \\
&+ \beta_4 Log\ Tranche\ Value_{j(t)} \\
&+ \beta_5\ Log\ Transaction\ Value_{i(t)} \\
&+ \beta_6\ Frequent\ Originator_{i(t)} \\
&+ \ Credit\ Rating, Year, and\ Security\ Type\ Controls_{ij(t)} \\
&+ \ \varepsilon_{ij(t)}
\end{aligned}
\tag{6.4}
$$

where ϵ_{ijt} is the idiosyncratic error term. The data vary by year *(t)*, deal *(i)* and security *(j).*

Third, to investigate if investors consider the risk retention methods in pricing the tranche beyond the credit rating, we use ordinary least square regressions with the issuance *Spread* (in basis points above the benchmark) as the dependent variable. The spread equals the quoted margin between the benchmark rate agreed upon at the date of pricing and the coupon of the initial spread, measured in basis points (bps). Similar to our third and fourth model, we also use *Risk Retention Methods* as the key independent variable. For our fifth model, we create a specific sample to be able to precisely measure pricing at issuance. First, we exclude all fixed-rate securities in our sample (325 tranches). As for fixed-rate tranches it is necessary to determine the appropriate benchmark yield curve for each tranche in the sample to get an issuance spread measure that is comparable with those of the floating-rate tranches. To avoid this problem, we restrict our sample to floating-rate tranches only. Second, we exclude all securities that are issued at a price different from par (228 tranches). Securities can be sold above or below par at issuance, therefore the par spreads are not always equal to the primary issuance spread (Hu & Cantor, 2006). To make sure that the quoted margin between the benchmark rate agreed upon at the date of pricing and the coupon of the initial yield represents the spread, we only include tranches that are issued exactly at par. The remaining 354 tranches constitute our *pricing subsample* used to test our third hypothesis. We use several variables to control for security-specific factors. We again control for the security-design characteristics (*No. of Tranches*, *Log Tranche Value*, *Log Transaction Value* and *Subordination*), *Frequent Originator*, *Year* and *Security Type*. In addition, we also control for the type of market wide *Benchmark Rate* used, the Euro Interbank Offered Rate (EURIBOR) at the date of issuance for the tranches in our sample (e.g., EURIBOR 3-months) and for the risk embedded in the securitization structure, which is proxied by the *Credit Rating*. The specification of fifth model is:

$$
\begin{aligned}
Spread_{j(t)} = \beta_0 &+ \beta_1 Risk\ Retention\ Methods_{i(t)} \\
&+ \beta_2 Subordination\ Level_{j(t)} + \beta_3 No.of\ Tranches_{i(t)} \\
&+ \beta_4 Log\ Tranche\ Value_{j(t)} \\
&+ \beta_5\ Log\ Transaction\ Value_{i(t)} \\
&+ \beta_6 Rating\ Discrepancy_{j(t)} \\
&+ \beta_7\ Frequent\ Originator_{i(t)} + \beta_8\ Benchmark\ Rate_{i(t)} \\
&+ Credit\ Rating, Year, and\ Security\ Type\ Controls_{ij(t)} \\
&+ \varepsilon_{ij(t)}
\end{aligned}
\tag{6.5}
$$

where ϵ_{ijt} is the idiosyncratic error term. The data vary by year *(t)*, deal *(i)*, and security *(j)*. Because the error terms have systematic heterogeneity in our estimation, we use a heteroskedasticity-consistent covariance matrix as suggested by White (1980).[77]

6.4 Data observations and trends

6.4.1 **Issuers' choices of risk retention methods**

The reason for originators (mostly banks) to issue securitizations could be manifold. Similarly, the optimal structure of a securitization for the originator, including the risk retention method, may depend on various aspects such as the capital position, funding profile, taxes as well as business model considerations. Due to lack of data on the internal cost of capital and funding calculations, the choice of the risk retention method cannot be statistically linked to a specific securitization motive. Yet, some considerations might give a direction of the strategies used by banks to select a specific risk retention method. For example, when banks face a capital constraint or seek to maximize capital relief for other reasons, the maximum capital relief is obtained by derecognizing the underlying

[77] Due to data limitations, we were not able to include the risk retention level as a control variable in our study.

assets. Thus, a significant risk transfer needs to be undertaken and the equity and mezzanine tranches need to be sold to comply with regulatory thresholds (see EBA, 2014a). The VES and OBS methods are the most appropriate risk retention methods to achieve the capital relief. In the VES (OBS) method, the issuers retain a part of each tranche (a selection of loans), having to hold capital based on the risk-weighted assets calculations for these parts (loans) only. While for the FLT and FLE method, the bank needs to deduct the entire retained part from its capital. In line with this, literature also states that the VES method appears to be most used if one aims for capital relief (see, e.g., HM Treasury, 2021). This could be a possible explanation for the rise of securitizations that use the VES method after 2017 (see Figure 6.3(b), Section 6.3.1), as securitizations compliant with the STS criteria can benefit from a more preferential treatment in capital requirements for securitization tranches (except for the equity tranche). As such, if banks were to seek capital relief, the VES method is even more attractive when combining with STS compliance.

We now seek to analyze this trend in more detail via a regression analysis. The results of our logit regressions as shown in Equation (6.1) are provided in Table 6.3, where *FLT vs. VES* is our dependent variable and *STS Compliant* our key independent variable. Column (1) presents the results for the full sample of all deals that have received either the FLT or VES retention method between 2014-2021. In column (2), we report the results of the deals that were issued before the introduction of the Securitization regulation (2014-2017) and in column (3) all those thereafter (2018-2021).

The results in column (1) of Table 6.3 show that we do not find any significant results for our *STS compliant* variable. However, the year dummies suggest that tranches are more likely to have the VES method starting in 2018[78], which is the year when the Securitization regulation came into force. *Country of Risk* and *GDP Growth Rate* are no statistically significant drivers for choosing VES over FLT.

[78] The detailed regression results including the security type and year dummies are available upon request.

Large or frequent originators have a higher likelihood of selecting the VES method, compared to the FLT method. We observe positive odds ratios of 0.75 (z-stat= 3.07) for *Frequent Originator*, statistically significant at the 1% level. Interestingly, looking at the deal attributes, all variables are significantly influencing the probability of choosing VES. The number of tranches increases the likelihood of choosing VES, and for security type, we find that CMBS tranches have a higher likelihood of having a VES method, compared to ABS. While CLO and RMBS have a higher likelihood of having the FLT method. An increase in the riskiness of the underlying pool also increases the likelihood of choosing VES. This indicates that the choice of selecting VES or FLT seems not to be mainly driven by the capital relief motive, and also not to be influenced by the country or economic development in the country of risk. Rather, it seems to be influenced by the securitization year, the originator's size, and deal attributes. Interestingly, when we split our sample between the period before (column 2) and after (column 3) the introduction of the Securitization regulation, we only find positive significant results for *Frequent Originator* in the period after. This suggests that the more experienced, frequent, originators were more likely to select the VES method after the introduction of the Securitization regulation, but not necessarily before.

Table 6.3: Logit regressions of FLT vs. VES method on frequent originator and STS compliant (deal-level analysis).

This table reports logit regressions of the risk retention methods on deal level characteristics at issuance, controlled for credit rating, security type, year and country controls. 'Horizontal vs. Vertical' is a dummy variable that equals 1 if the tranche retainer of the deal holds at least 5% material net economic interest via the VES method, and 0 if the FLT method is used. 'Frequent Originator' is a dummy that equals 1 if the tranche's originator is among the top 10% measured by number of tranches contributed to the total number of securities issued in the EU (2011-2021), and 0 otherwise. 'STS Compliant' is a dummy that equals 1 if the deal is compliant with STS criteria at the time of issuance, and 0 otherwise. 'No. of Tranches' is the total number of tranches in the securitization of which the security is part of. 'Single Originator' is a dummy indicating 1 if the deal is originated by a single originator, and 0 if originated by multiple originators. 'GDP Growth Rate' is the annual percentage growth rate of GDP in the country to which the risks of the securitization are exposed to. 'Credit Rating' represents the average credit rating provided by Moody's, S&P, Fitch, DBRS and KBRA. We have converted the ratings into a numerical value by setting 1 for Aaa, 2 for Aa2, 3 for Aa2, and so on. 'Security Type' represents the type of securitization of the deal, ranging from ABS, RMBS, CMBS, to CLO. 'Year' represents the year in which the deal is issued. 'Country of Risk' is the country to which the (majority of the) securitization's risks are exposed to. Z-statistics are reported in parentheses in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	2014-2021	*2014-2017*	*2018-2021*
	(1)	(2)	(3)
Frequent Originator	0.75***	0.44	0.89***
	(3.07)	(0.89)	(2.86)
STS Compliant	0.09		0.26
	(0.31)		(0.76)
No. of Tranches	0.48***	0.19**	0.68***
	(8.58)	(2.01)	(8.69)
Single Originator	-0.04	-0.49	0.25
	(-0.11)	(-0.84)	(0.58)
GDP Growth Rate	-0.01	0.09	-0.05
	(-0.13)	(1.36)	(-0.89)
Credit Rating	Y	Y	Y
Security type	Y	Y	Y
Year	Y	Y	Y
Country of Risk	Y	Y	Y
Observations	703	223	402
Pseudo R-squared	0.336	0.0575	0.362

6.4.2 **Risk retention methods and security design**

The results of our t-tests based on the estimates of Equation (6.2) are provided in Table 6.4. We compare the security design of the tranches that have the FLT as the retention method with those that have the VES, OBS, and FLE retention method. Panel A of Table 6.4 suggests that the security design significantly differs between the retention methods. In particular, we observe that both the VES and OBS methods have, on average, significantly i) higher number of tranches in a deal; ii) lower tranche size; and iii) lower transaction size, compared to the FLT method. For example, the average transaction size for the FLT method is €1.210 million, while the size is significantly smaller for the VES and OBS method, with €954 million and €1.030 million, respectively. For the FLE method, we only observe that securitization with the FLE method have, on average, a significantly higher number of tranches in a deal (4.87 tranches), compared to the FLT method (4.11 tranches). In sum, securitizations with the VES and OBS method seem to have lower tranche and transaction sizes, but a greater number of tranches in a deal, while securitizations with the FLE method seem to have a greater number of tranches in a deal than those with the FLT method.

Next, we split our 'full' sample between tranches issued by frequent (larger) originators, Panel B, and those issued by infrequent (smaller) originators, Panel C. We observe that the security design characteristics of the various risk retention methods differ to a greater extent for the frequent originators than for infrequent ones. For example, we observe that for frequent originators, securitizations with the VES and OBS method have significantly higher number of tranches and lower tranche and transaction size, than the FLT method. For the FLE method, we observe that these securitizations have, on average, higher tranche counts and lower subordination levels, compared to the FLT method. While for the infrequent originators (Panel C), we only find significant differences for the number of tranches and tranche size of the VES and OBS method. In addition, we observe

Table 6.4: T-tests of risk retention methods and security design factors (tranche-level analysis).

This table reports t-tests of the risk retention methods and the security design factors. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. 'No. of Tranches' is the total number of tranches in the securitization of which the security is part of. 'Log Tranche Value' is the natural logarithm of the tranche value at issuance, measured in Euro. 'Log Transaction Value' is the natural logarithm of the transaction value of the deal at issuance, measured in Euro. 'Subordination Level' represents the level of internal credit enhancement supporting the security within a securitization, measured as the ratio of all tranches subordinated to the tranche in question divided by the total value of the securitization.

Panel A: Full tranche-level sample

		FLT vs. VES		*FLT vs. OBS*		*FLT vs. FLE*	
	FLT	**VES**	**T-test *p-value***	**OBS**	**T-test *p-value***	**FLE**	**T-test *p-value***
Security design factors	*Mean*	*Mean*		*Mean*		*Mean*	
No. of Tranches	4.11	7.23	0.0000	4.92	0.0000	4.87	0.0102
Tranche Size (in mio)	626	243	0.0000	298	0.0000	534	0.4764
Transaction Size (in mio)	1210	954	0.0031	1030	0.0480	1640	0.0947
Subordination (in %)	0.26	0.25	0.7063	0.27	0.5332	0.22	0.1216
Observations	1045	735		323		54	

Panel B: Frequent Originators Only

		FLT vs. VES		*FLT vs. OBS*		*FLT vs. FLE*	
	FLT	**VES**	**T-test *p-value***	**OBS**	**T-test *p-value***	**FLE**	**T-test *p-value***
Security design factors	*Mean*	*Mean*		*Mean*		*Mean*	
No. of Tranches	3.93	7.24	0.0000	4.64	0.0004	4.81	0.0328
Tranche Size (in mio)	654	207	0.0000	285	0.0000	581	0.7086
Transaction Size (in mio)	1410	1020	0.0028	903	0.0000	1900	0.1941
Subordination (in %)	0.26	0.26	0.8670	0.31	0.0949	0.18	0.0055
Observations	500	427		213		31	

Panel C: Infrequent Originators Only

		FLT vs. VES		*FLT vs. OBS*		*FLT vs. FLE*	
	FLT	**VES**	**T-test** ***p-value***	**OBS**	**T-test** ***p-value***	**FLE**	**T-test** ***p-value***
Security design factors	*Mean*	*Mean*		*Mean*		*Mean*	
No. of Tranches	4.27	7.21	0.0000	5.50	0.0000	4.96	0.1177
Tranche Size (in mio)	599	293	0.0001	325	0.0008	471	0.4119
Transaction Size (in mio)	1020	863	0.1387	1280	0.1249	1300	0.4225
Subordination (in %)	0.26	0.25	0.6681	0.20	0.0385	0.27	0.8454
Observations	545	308		110		23	

that for infrequent originators, the subordination level of securitization with the OBS method is slightly lower than for the FLT method. There are no significant differences between the FLE and FLT method for infrequent originators.

6.5 Empirical Results

The results of our first regression model, Equation (6.3), are shown in Table 6.5. In Table 6.5, we report the results of the ordered logit regressions with *Credit Rating* as the dependent variable and *Risk Retention Methods* as key independent variable. The results of our second regression model, Equation (6.4), are shown in Tables 6.6 and 6.7. In these tables, we report the results of the ordered logit regressions with *Rating Discrepancy* as the dependent variable and *Risk Retention Methods* as key independent variable. The results of our third regression model, Equation (6.5), are provided in Tables 6.8 and 6.9. In Tables 6.8 and 6.9, we use the issuance *Spread* as the dependent variable, and *Risk Retention Methods* as the key independent variable. In all our models, the independent variable *Risk Retention Methods* is of categorical nature. Where we report the values for only VES, OBS and FLE, as the FLT is the omitted variable.[79]

6.5.1 **Risk retention methods and credit ratings**

We first analyze if the credit ratings of CRAs differ for securitization tranches with different risk retention methods. The results of our ordered logit regressions are provided in Table 6.5, where *Credit Rating* is our dependent variable and the *Risk Retention Methods* our key independent variable. Panel A presents the results of our model using the full tranche-level sample (column 1) and the results for tranches with frequent (column 2) and infrequent (column 3) originators. In Panel B, we show the results for the credit ratings of Moody's (column 1), S&P (column 2), DBRS (column 3) and Fitch (column 4) separately.[80]

[79] We use the first loss tranche method as the baseline as this method is used most in our sample.
[80] The number of observations for KBRA are too limited to do statistical analyses.

The results in column (1), Panel A of Table 6.5, show that the credit rating is, on average, worse for tranches with a VES method than for tranches with a FLT method. We observe positive odds ratios of -0.69 (z-stat= 6.18) for the VES method, statistically significant at the 1% level. We find consistent results when we split our sample between tranches with frequent originators in column (2), and those with infrequent originators in column (3). These results indicate that CRAs assign worse credit ratings for VES, on average, than for tranches with the FLT method. Interestingly, we find that only for tranches with frequent originators, CRAs assign a worse rating on average for tranches with the FLE method, compared to the FLT method, with positive odd ratios of 1.13 (z-stat= 3.17) significant at the 1% significance level. We do not find highly significant results for OBS. In our robustness analysis, column (1) of Table I, Appendix II, we repeat the analysis of Table 6.4 but now include the following additional control variables; *STS Compliant*, *Single Originator*, *GDP Growth Rate* and *Country of Risk* controls. We show that our results of Table 6.4 remain robust when including several additional controls to our model.

Given data limitations, it is difficult to determine the exact reason for our findings. It could be that the underlying pool is on average riskier for VES transactions.[81] In the FLT method, the retainer takes a significantly larger share of the first losses compared to the VES method, which can be interpreted as a signal to markets for confidence of the retainer in the underlying pool.

We observe slightly different results when comparing the credit ratings of each CRA separately in Panel B of Table 6.5. The results show that Moody's (column 1), S&P (column 2), and DBRS (column 3) all assign a worse rating, on average, for tranches with the VES method, compared to the FLT method. A result consistent

[81] Following discussions with major rating agencies, it seems that CRAs do not specifically consider the different risk retention methods in their credit rating models and, as such, it appears that the credit rating represents the riskiness of the underlying portfolio, rather than the risk retention method itself that is seen as creating higher risks for investors (e.g. because of the return profiles and incentives associated to them).

with Panel A. However, we do not find any significant result for Fitch (column 4). We observe positive odds ratios of 0.53 (z-stat= -3.40) for Moody's, 1.27 (z-stat= -6.54) for S&P, and 0.38 (z-stat= -2.83) for DBRS, all significant at the 1% significance level. The results also show that S&P assigns worse ratings, on average, for tranches with the FLE method compared to tranches with the FLT method, with odds of 1.46, column (2) of Panel B. However, the results for the FLE method should be interpreted cautiously as only a relatively small percentage (2.50%) of tranches in our sample used the FLE method. We find similar results for tranches with a credit rating from Moody's, column (1) of Panel B, albeit only at the 5% significance level.

Next, we analyze if there is a disagreement between the credit rating of different CRAs (i.e., rating discrepancy or split ratings), considering the risk retention method applied by the tranche retainer. Rating discrepancy arises when two or more CRAs report different credit ratings for the same tranche at issuance (e.g., a tranche received an AAA rating of Moody's and an AA rating of S&P).[82] We therefore only include those tranches in our model that have received two or more credit ratings at issuance in our regression model.[83] The results of our ordered logit regressions are provided in Table 6.6, where *Rating Discrepancy* is our dependent variable and the *Risk Retention Methods* our key independent variable. In columns (1) to (5) we subsequently include control variables, where column (5) presents our full model including several controls for security-design characteristics, credit rating, year, and security type.

Our results in column (5) show that rating discrepancy is lower for tranches with a VES and FLE method, compared to the FLT method. We observe negative odds ratios of -0.52 (z-stat= -3.74) for the VES method, statistically significant

[82] Rating discrepancy can also be a result of CRAs assigning better ratings as a strategy to win business from its competitors (see, e.g., Van Breemen et al., 2023).
[83] If the tranche received more than two credit ratings, we measured rating discrepancy by taking the highest and lowest credit rating. If we only include dual-rated tranches in our sample, we obtain similar results.

at the 1% level. This indicates that CRAs are more likely to report ratings that are the same for the VES method than for the FLT method. Similarly, we find a negative and highly significant coefficient for FLE, with odds of -1.05 (z-stat= -3.43). While for the OBS method, we find no significant results at all, column (5). Our results are robust when we exclude our security design characteristics and originators' size variable in columns (1) to (4). These results suggests that CRAs have less rating disagreement for tranches with the VES and FLE method, relative to our base method FLT. So apparently, CRAs find it more difficult to evaluate the credit risk of tranches with the FLT method. In our robustness analysis, column (2) of Table I, Appendix II, we repeat the analysis of Table 6.6 but now include the following additional control variables; *STS Compliant*, *Single Originator*, *GDP Growth Rate* and *Country of Risk* controls. We show that our results of Table 6.6 remain robust when including several additional controls to our model.

In Table 6.7, we again repeat the analysis of Table 6.6, but we split our sample between tranches that are originated by frequent originator (i.e., originators among the top 10% measured by number of tranches), columns (1) and (2), and those who are originated by infrequent originators (the remaining 90%), columns (3) and (4). We do so to analyze if CRAs are sensitive to the size and experience of the originator by assigning split ratings for specific risk retention methods.

Interestingly, we show that CRAs indeed deviate between the size of originators when assigning split ratings for specific risk retention methods. Remarkably, when we look at the frequent originators, we find no highly significant results for VES and OBS in columns (1) and (2). While for FLE, we find a negative significant coefficient, with odds ratios of -0.88 (z-stat= -2.24), albeit at the 5% level, column (2). However, when we remove our set of independent variables, in column (1), our results turn insignificant. Henceforth, when a tranche is originated by a frequent (more experienced) originator, CRAs are less likely to have rating disagreements when it comes to the different risk retention methods.

While for infrequent originators, we observe negative odds ratios of -0.48 (z-stat= -2.31) for the VES method, significant at the 5% significance level, column (4) of Table 6.7. Similarly, we find negative significant results for FLE, with odds of -1.54, in column (4). The results remain consistent only for FLE when we remove our set of independent variables in column (1). The results suggest that CRAs mainly seem to have less disagreements for tranches with the FLE method that are originated by infrequent originators. In line with Table 6.6, we find no significant results for OBS in Table 6.7. Hence, CRAs do not seem to experience less or more disagreements between credit ratings of tranches with the OBS method, compared to the FLT method.

To summarize, we find that credit ratings are worse, on average, for the VES method than for tranches with the FLT method. We also find that, for tranches with frequent originators or those with an S&P rating, the credit ratings are on average worse for the FLE method, compared to the FLT method. In addition, we find that rating disagreements amongst CRAs is less likely, on average, for the VES and FLE method than for the FLT method. However, we find that rating disagreement is particularly lower for tranches that are originated by infrequent originators. So apparently, CRAs report stricter ratings and experience fewer rating disagreements for tranches with the VES and FLE method, than for tranches with the FLT method. Tranches with the FLT method seem to have better ratings, on average, but CRAs seem to misalign in their credit risk assessment more often and report split ratings as a result.

6.5.2 **Risk retention methods and spread at issuance**

The sole purpose of the risk retention rule was to better align the interest between the originator and investor, by requiring originators to have a significant portion of *skin-in-the-game*. This might incentivize the originators to do 'do their jobs better', for example, by improving their screening and monitoring standards. As originators are allowed to apply multiple methods to retain skin-in-the-game, we seek to investigate if investors perceive these methods to be equally risky or not. We do so by analyzing if investors deviate in their pricing (measured by issuance spread) between the different risk retention methods.

In Table 6.8, we report the results of the ordinary least square regressions with *Spread* at issuance as our dependent variable and the *Dummy Risk Methods* as the key independent variable. Our results show that for tranches with a VES method, investors tend to reduce their issuance spread compared to the FLT method, with a coefficient of -27.45 (*t-stat*= -2.40), significant at the 5% level. Hence, tranches with the VES method receive on average a spread at issuance that is remarkably lower, with 27.45 basis points, than those with the FLT method. Similarly, for the OBS risk retention method, compared to the FLT method, investors reduce the spread at issuance, with a coefficient of -36.08 (*t-stat*= -4.61), column (5). Thus, investors also demand a significantly lower issuance spread, with 36.08 basis points on average, for tranches with the OBS method, relative to the FLT method. We find consistent results significant at the 1% level for both variables when we remove our controls in columns (1) to (4). For FLE we do not find consistent (highly) significant results throughout columns (1) to (5). Hence, it appears that investors look beyond the credit rating and adjust their issuance spread when the originator applies the VES and OBS method to retain skin-in-the-game. While we find no highly significant impact on pricing for the FLE method. So, it appears that while controlling for the credit rating, investors find the VES and OBS method less risky and potentially better aligning the interests between the originator and investor.[84]

[84] In column (3) of Table I, Appendix II, we repeat the analysis of Table 6.8 by including the following additional control variables for robustness purposes; STS Compliant, Single Originator, GDP Growth Rate and Country of Risk controls. We show that our results of Table 6.8 remain robust when including several additional controls to our model.

As a next step, in Table 6.9, we repeat the analysis of Table 6.8 but now we split our sample between tranches originated by frequent originators, columns (1) and (2), and those originated by infrequent originators, columns (3) and (4). We find some remarkable results. Only for frequent originators, investors seem to adjust their pricing for the different risk retention methods. In column (2), we show that investors lower their spread, with a coefficient of -45.91 (*t-stat*= -3.00), when the tranche retainer has applied the VES method. This indicates that tranches with the VES method that are issued by a frequent originator receive, on average, a 45.91 basis points lower issuance spread than tranches with the FLT method that are issued by frequent originators. We find consistent results for the OBS method, where investors reduce their issuance spread, with a coefficient of -34.23 (*t-stat*= -3.28), compared to the FLT method. Consistent with Table 6.8, we find no significant results for the FLE method. Interestingly, if we move to the tranches originated by infrequent originators, columns (3) and (4), we find no significant results at all for our risk retention method variables. This suggests that investors do not adjust their spread at issuance for any of the different risk retention methods when the tranche originator is smaller in terms of size (measured by the number of tranches).

In sum, we find that investors do not value the different risk retention methods as equally risky. We find that taking into account the ratings, spreads seem to be highest for FLT, given that for VES and OBS (and in parts for FLE) the coefficients are significantly negative. This result is in line with our expectations. The loss and return profile of the OBS and VES method seem to (mathematically) best align the interest between the retainer and investor over time, while least alignment seem to be achieved for the FLT method (Section 6.2.3 and Appendix I). It might well be that investors observing the assigned credit ratings before making their investment choices, take into account the on average better rating of FLT transactions (see Table 6.5) and compensate for the additional risks that come with the FLT method (e.g., sufficient portfolio management over time). While perhaps CRAs focus, in their risk assessment, mainly on credit risks to which the underlying portfolio is exposed to, rather than the proper alignment of risks between the retainer and investor over time. Hence, they might consider the FLT method as least risky as the retainer holds the portion of the securitization that bears the highest risk, which can also be interpreted as a signal of confidence by the retainer, given that his retention is lost when the equity tranche is 'eaten up'.

Overall, we can conclude that the different risk retention methods do not have an equal risk profile and, as a result, impact the credit ratings and prices of securitization tranches at issuance.

Table 6.5: Ordered logit regressions of risk retention methods on credit ratings (tranche-level analysis).

This table reports ordered logit regressions of the risk retention methods on the credit rating at issuance, controlled for security-design characteristics as well as year and security type controls. 'Credit rating' represents the average credit rating of Moody's, S&P, Fitch, DBRS, and KBRA converted into a numerical value by setting 1 for Aaa, 2 for Aa1, 3 for Aa2, and so on. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. The FLT method is the omitted variable. All other control variables are defined in Table 6.2. Z-statistics are reported in parentheses in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

Panel A – Full tranche-level sample and sorted by originators' size

	Full sample	*Frequent Originator*	*Infrequent Originator*
	(1)	(2)	(3)
VES	0.69***	0.70***	0.82***
	(6.18)	(4.04)	(5.30)
OBS	-0.20	-0.28*	0.03
	(-1.63)	(-1.67)	(0.17)
FLE	0.45*	1.13***	-0.56
	(1.74)	(3.17)	(-1.44)
Subordination Level	-0.35**	-0.59***	0.45*
	(-2.39)	(-3.03)	(1.84)
No. of Tranches	-0.08***	-0.11***	-0.08***
	(-4.06)	(-3.45)	(-2.66)
Log Tranche Value	-0.94***	-1.00***	-0.93***
	(-26.79)	(-20.91)	(-17.30)
Log Transaction Value	0.72***	0.91***	0.51***
	(12.22)	(10.76)	(5.51)
Frequent Originator	-0.43***		
	(-5.13)		
Rating Discrepancy	0.27***	0.25***	0.29***
	(9.17)	(6.32)	(6.24)
Year	Y	Y	Y
Security Type	Y	Y	Y
Observations	2,157	1,171	986
Pseudo R2	0.121	0.132	0.126

Table 6.5 continued

Panel B - Sorted by CRAs

	Moody's	*S&P*	*DBRS*	*Fitch*
	(1)	(2)	(3)	(4)
VES	0.53***	1.27***	0.38***	0.30
	-3.40	-6.54	-2.83	(1.37)
OBS	-0.11	-0.02	-0.15	-0.45**
	(-0.71)	(-0.07)	(-0.91)	(-2.12)
FLE	1.17**	1.46***	0.02	-0.03
	-2.26	-3.48	-0.09	(-0.07)
Subordination Level	-0.39*	0.21	-0.84***	-0.17
	(-1.93)	-0.84	(-4.39)	(-0.65)
No. of Tranches	-0.05*	-0.04	-0.13***	0.00
	(-1.90)	(-1.12)	(-5.18)	(0.01)
Log Tranche Value	-0.89***	-1.09***	-0.92***	-0.96***
	(-19.27)	(-17.36)	(-20.00)	(-14.58)
Log Transaction Value	0.78***	0.61***	0.73***	0.75***
	-9.33	-6.61	-9.99	(6.72)
Frequent Originator	-0.49***	-0.38***	-0.25**	-0.417**
	(-4.20)	(-2.61)	(-2.42)	(-2.49)
Rating Discrepancy	0.29***	0.27***	0.24***	0.51***
	-7.41	-5.32	-5.57	(9.55)
Year	Y	Y	Y	Y
Security Type	Y	Y	Y	Y
Observations	1,183	856	1,385	744
Pseudo R2	0.124	0.179	0.100	0.178

Table 6.6: Ordered logit regressions of risk retention methods on rating discrepancy (tranche-level analysis).

This table reports ordered logit regressions of the risk retention methods on the rating discrepancy at issuance, controlled for security-design characteristics as well as credit rating, year and security type controls. 'Rating Discrepancy' represents the notches difference that results from calculating the numerical difference in credit rating of Moody's, S&P, Fitch, DBRS and KBRA. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. The FLT method is the omitted variable. All other control variables are defined in Table 6.2. Z-statistics are reported in parentheses in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
VES	-0.35***	-0.43***	-0.32***	-0.50***	-0.52***
	(-3.12)	(-3.65)	(-2.58)	(-3.64)	(-3.74)
OBS	-0.12	-0.14	-0.05	-0.17	-0.18
	(-0.77)	(-0.91)	(-0.30)	(-1.05)	(-1.13)
FLE	-0.80***	-0.85***	-0.86***	-1.04***	-1.05***
	(-2.71)	(-2.84)	(-2.86)	(-3.40)	(-3.43)
Subordination Level				-0.33*	-0.35*
				(-1.71)	(-1.79)
No. of Tranches				0.06**	0.06**
				(2.16)	(2.26)
Log Tranche Value				-0.11**	-0.10**
				(-2.45)	(-2.23)
Log Transaction Value				0.39***	0.37***
				(4.88)	(4.50)
Frequent Originator					0.10
					(0.95)
Credit Rating	Y	Y	Y	Y	Y
Year	N	Y	Y	Y	Y
Security Type	N	N	Y	Y	Y
Observations	1,865	1,865	1,865	1,865	1,865
Pseudo R-squared	0.188	0.192	0.195	0.202	0.202

Table 6.7: Ordered logit regressions of risk retention methods on rating discrepancy - Sorted by originators' size (tranche-level analysis).

This table reports ordered logit regressions of the risk retention methods on the rating discrepancy at issuance, controlled for security-design characteristics as well as credit rating, year and security type controls. 'Rating Discrepancy' represents the notches difference that results from calculating the numerical difference in credit rating of Moody's, S&P, Fitch, DBRS and KBRA. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. The FLT method is the omitted variable. All other control variables are defined in Table 6.2. Z-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	Frequent Originator		*Infrequent Originator*	
	(1)	(2)	(3)	(4)
VES	-0.24	-0.39*	-0.34*	-0.48**
	(-1.28)	(-1.82)	(-1.77)	(-2.31)
OBS	0.02	-0.04	0.12	0.01
	(0.09)	(-0.17)	(0.46)	(0.03)
FLE	-0.58	-0.88**	-1.44***	-1.54***
	(-1.53)	(-2.24)	(-2.66)	(-2.83)
Subordination Level		-0.14		-0.34
		(-0.58)		(-0.97)
No. of Tranches		0.08*		0.05
		(1.94)		(1.25)
Log Tranche Value		-0.09		-0.10
		(-1.53)		(-1.30)
Log Transaction Value		0.50***		0.19
		(4.47)		(1.49)
Credit Rating	Y	Y	Y	Y
Year	Y	Y	Y	Y
Security Type	Y	Y	Y	Y
Observations	1,050	1,050	815	815
Pseudo R-squared	0.208	0.218	0.202	0.205

Table 6.8: Ordinary least squares regressions of risk retention methods on spread at issuance (floting-rate tranches only).

This table reports ordinary least squares regressions of the risk retention measures on the spread at issuance, controlled for security-design characteristics as well as credit rating, year and security type controls. 'Spread' is the quoted margin between the benchmark rate and the coupon of the initial spread, in basis points. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. The FLT method is the omitted variable. All other control variables are defined in Table 6.2. White (1980) heteroskedasticity-adjusted t-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
VES	-53.18***	-51.64***	-49.68***	-43.68***	-27.45**
	(-5.35)	(-4.70)	(-4.62)	(-4.50)	(-2.40)
OBS	-45.30***	-46.42***	-41.45***	-39.33***	-36.08***
	(-5.16)	(-4.52)	(-4.24)	(-5.07)	(-4.61)
FLE	-38.59***	-28.69*	-39.54**	-11.91	-6.85
	(-3.46)	(-1.88)	(-2.56)	(-0.89)	(-0.48)
Subordination Level				-12.52	-19.87
				(-0.93)	(-1.44)
No. of Tranches				-2.130	-2.28
				(-0.96)	(-1.08)
Log Tranche Value				-27.97***	-25.45***
				(-7.53)	(-6.77)
Log Transaction Value				28.15***	28.71***
				(5.54)	(5.84)
Rating Discrepancy				18.67***	17.55***
				(6.01)	(5.63)
Benchmark Rate				15.82	15.30
				(1.22)	(1.15)
Frequent Originator					27.07***
					(3.25)
Credit Rating	Y	Y	Y	Y	Y
Year	N	Y	Y	Y	Y
Security Type	N	N	Y	Y	Y
Observations	354	354	354	354	354
R-squared	0.703	0.707	0.725	0.804	0.811
Adjusted R-squared	0.686	0.680	0.697	0.780	0.787

Table 6.9: Ordinary least squares regressions of risk retention methods on spread at issuance (floating-rate).

This table reports ordinary least squares regressions of the risk retention measures on the spread at issuance, controlled for security-design characteristics as well as credit rating, year and security type controls. 'Spread' is the quoted margin between the benchmark rate and the coupon of the initial spread, in basis points. 'Risk Retention Methods' is a categorical variable indicating the form in which the 5% material net economic interest is obtained, which includes the 'VES', 'OBS', 'FLT' or 'FLE' method. The FLT method is the omitted variable. All other control variables are defined in Table 6.2. White (1980) heteroskedasticity-adjusted t-statistics are reported in parentheses and (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	Frequent Originator		*Infrequent Originator*	
	(1)	(2)	(3)	(4)
VES	-73.65***	-45.91***	19.36	16.17
	(-4.46)	(-3.00)	(1.34)	(1.32)
OBS	-49.26***	-34.23***	-7.70	-17.27
	(-4.16)	(-3.28)	(-0.76)	(-1.49)
FLE	-42.34	19.90	-12.95	-9.21
	(-1.35)	(0.62)	(-0.82)	(-0.84)
Subordination Level		-74.56***		-13.00
		(-3.27)		(-0.72)
No. of Tranches		-7.41*		3.03
		(-1.92)		(1.50)
Log Tranche Value		-28.93***		-10.75**
		(-5.12)		(-2.01)
Log Transaction Value		37.47***		1.81
		(6.31)		(0.29)
Rating Discrepancy		17.15***		3.10
		(5.19)		(0.52)
Benchmark Rate		9.40		-1.28
		(0.56)		(-0.09)
Credit Rating	Y	Y	Y	Y
Year	Y	Y	Y	Y
Security Type	Y	Y	Y	Y
Observations	224	224	130	130
R-squared	0.782	0.873	0.902	0.922
Adjusted R-squared	0.747	0.847	0.874	0.893

6.6 Conclusion

In this paper, we investigate the impact of the different European regulatory risk retention methods on the credit ratings and pricing of securitization tranches at the time of issuance. The risk retention rule, that came into force as of 2011 for European securitization transactions, has the purpose to better align the interest between the originator and the investor. The current regulatory framework allows originators to use several methods to retain (at least) 5% of the securitization transaction. Currently, these methods receive an equal treatment (no differentiation amongst them is applied) by regulation and it is up to the retainer which method to apply.

With a large sample of European securitizations originated and sold between 2011 and 2021, we show that CRAs assign better credit ratings to securitizations using the FLT risk retention method. In addition, CRAs also experience rating disagreements (either more or less) depending on the tranches' risk retention method. Interestingly, also investors adjust their pricing at issuance for tranches with different risk retention method even after controlling for the credit rating. In particular, they demand lower spreads at issuance for tranches with the VES and OBS method, compared to the FLT method. This suggests that as expected, investors and CRAs unlike regulators do not perceive the different retention methods as having equal risk. Our results are of particular importance to regulators and supervisors and strongly suggest reconsidering the different risk retention methods and whether they should indeed be treated equally.

Future research could assess the inherent risks of the underlying pools in relation to the chosen risk retention method using loan level data. Another avenue for future research would be a theoretical model that takes into account the various payment structures of retainers and investors for the different methods.

6.7 Appendices

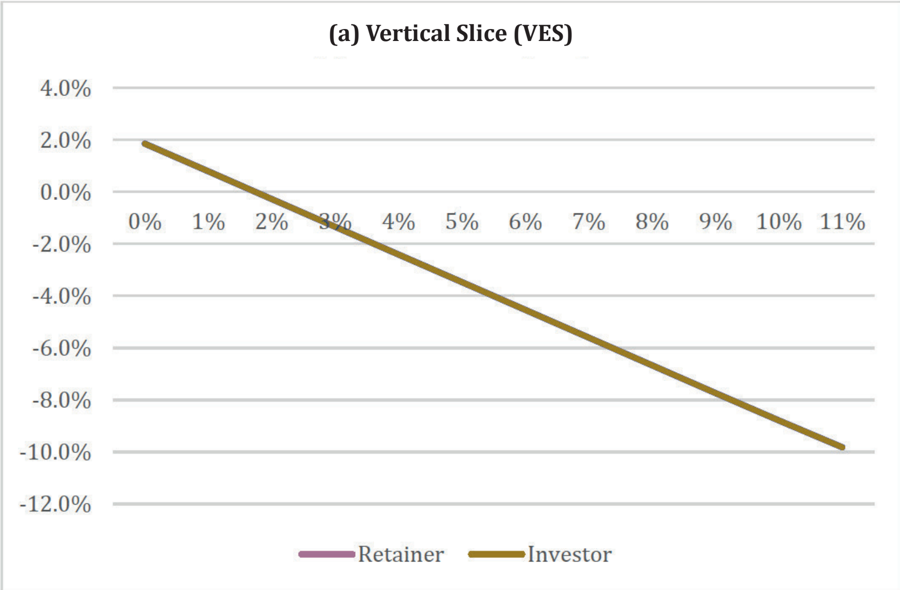
Appendix I. **Alignment of returns of retainer and investors: an example**

To illustrate the alignment between the investor and retainer, we show an example in Figure I of returns for the retainer and the investor along the total loss distribution for different retention methods. The results are simulated using a hypothetical securitization, but the overall conclusions also hold for other specifications and can be generalized. We consider the retainer to be the originator and we assume that two types of stakeholders (originator and investor) hold the entire assets. The loan pool is sufficiently diversified to assume that idiosyncratic risk is negligible. In our example, we also assume a risk-free rate of zero at 2 points in time (t=0 when the retention method is chosen and investments are made; t=1 when losses are realized and payoffs are distributed). Losses refer to the total losses (i.e., default rate times loss at default) and the risk retention of the retainer is equal to 5% of the total securitization.

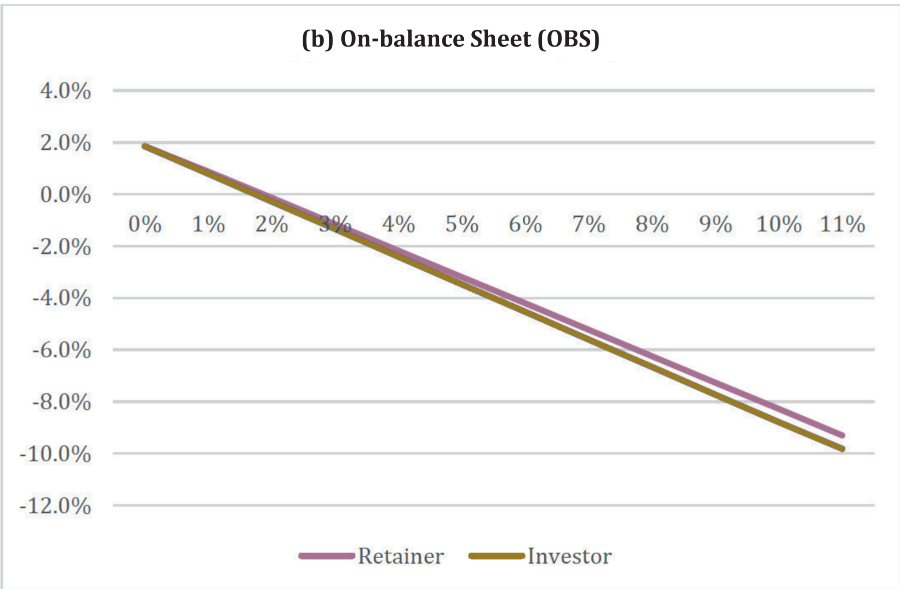
In this example: FLT: the retainer holds 5%, all invested in the equity tranche; FLE: the retainer sells the papers at a value of 95% and the 5% discount is refunded to him when the discounted sale amount is not entirely absorbed by losses; VES: the retainer holds 5% of each of the tranches; OBS: the retainer choses a truly randomly selected portion of 5% of the pool of loans that is kept on his books. The risk profile of the retained loans is assumed to be identical to the risk profile of the loans securitized and thus total losses are assumed to be equal. Interest income on the loans is assumed to be at 1.9% (matching the weighted average return of the securitization tranches).

The securitization is structured as follows:

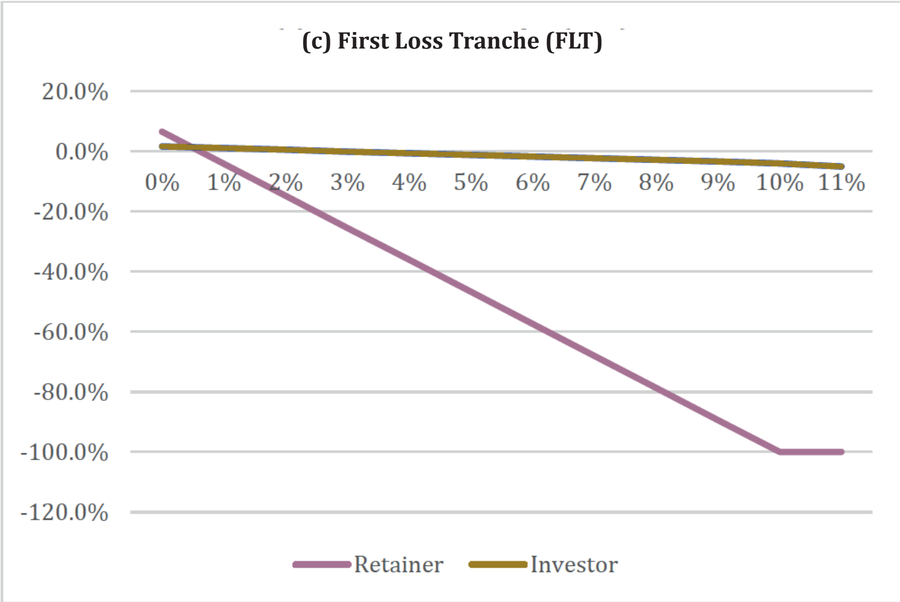
	Size	**Coupon**
Equity tranche	10%	6.5%
Mezzanine 1	12%	2.7%
Mezzanine 2	16%	1.9%
Mezzanine 3	20%	1.4%
Senior	42%	0.7%



(a) Vertical Slice (VES)
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
-8.0%
-10.0%
-12.0%
0% 1% 2% 3% 4% 5% 6% 7% 8% 9% 10% 11%
Retainer
Investor



(b) On-balance Sheet (OBS)
4.0%
2.0%
0.0%
-2.0%
-4.0%
-6.0%
-8.0%
-10.0%
-12.0%
0% 1% 2% 3% 4% 5% 6% 7% 8% 9% 10% 11%
Retainer
Investor



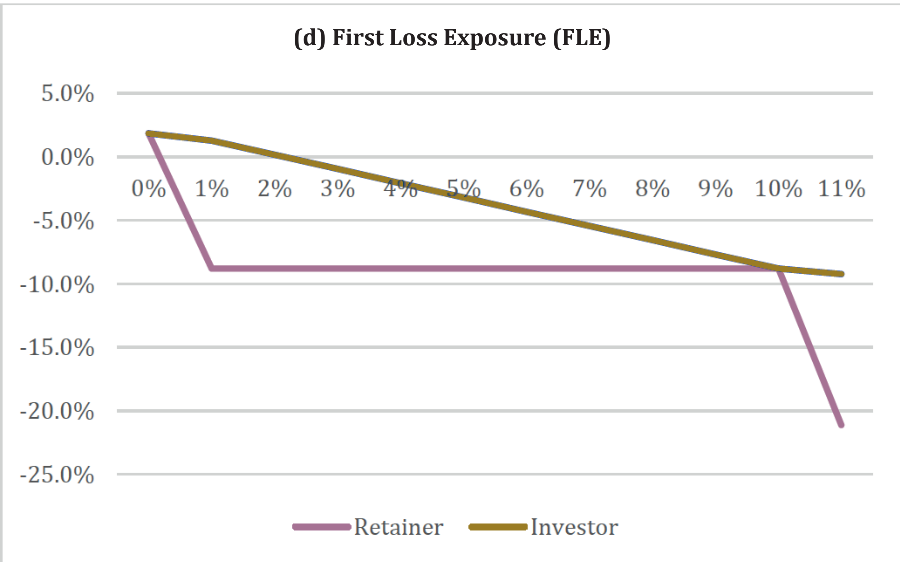


Figure I: Return function along the total loss distribution of the retainer and investor, sorted by risk retention method.

x-axis: total losses; y-axis: return at t=1

Appendix II. **Robustness Analyses**

Table I: Robustness analyses.

This table reports robustness analyses of the risk retention methods on our three key independent variables: Credit Rating, Rating Discrepancy and Spread. Column 1 reports ordered logit regressions of the risk retention methods on the credit rating at issuance (similar to Table 6.4). Column (2) reports ordered logit regressions of the risk retention methods on the rating discrepancy at issuance (similar to Table 6.6). Column (3) reports ordinary least squares regressions of the risk retention measures on spread at issuance (similar to Table 6.8). The following additional controls are included for robustness purposes; 'STS Compliant', 'Single Originator', 'GDP Growth Rate', 'Country of Risk' and 'Originator'. 'Originator' represents the originator of the securitization tranches. All other variables are defined in Tables 6.2 and 6.3. (*), (**), (***) denote significance levels of 10%, 5% and 1%, respectively.

	Credit Rating	*Rating Discrepancy*	*Spread*
	(1)	(2)	(3)
VES	0.59***	-0.55***	-33.51***
	(5.15)	(-3.79)	(-2.66)
OBS	-0.03	-0.23	-33.93***
	(-0.20)	(-1.37)	(-4.11)
FLE	0.42	-1.06***	-3.07
	(1.59)	(-3.43)	(-0.19)
Subordination Level	-0.62***	-0.25	-32.40**
	(-4.03)	(-1.27)	(-2.25)
No. of Tranches	-0.12***	0.07**	-2.70
	(-5.63)	(2.51)	(-1.27)
Log Tranche Value	-1.05***	-0.07	-25.97***
	(-28.19)	(-1.40)	(-7.07)
Log Transaction Value	0.82***	0.34***	30.20***
	(13.02)	(3.94)	(5.17)
Frequent Originator	-0.42***	0.10	32.89***
	(-4.48)	(0.85)	(2.99)
Rating Discrepancy	0.29***		17.88***
	(9.37)		(5.76)
Benchmark Rate			25.97*
			(1.76)
STS Compliant	-1.11***	0.51***	0.41
	(-8.98)	(3.23)	(0.04)
Single Originator	0.82***	0.08	-40.70***
	(4.70)	(0.36)	(-3.23)
GDP Growth Rate	0.02	-0.01	1.21
	(1.35)	(-0.54)	(1.24)
Credit Rating	Y	Y	Y
Year	Y	Y	Y
Security type	Y	Y	Y
Country of Risk	Y	Y	Y
Originator	Y	Y	Y
Observations	2,153	1,861	354
Pseudo R-squared	0.140	0.208	
Adjusted R-squared			0.791

References

Agarwal, S., Ambrose, B. W., Yildirim, Y., & Zhang, J. (2021). Risk retention rules and the issuance of commercial mortgage backed securities*. Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-021-09837-1

Bektić, D., & Hachenberg, B. (2021). European arbitrage CLOs and risk retention. *European Journal of Finance 27*(18), 1791-1803. https://doi.org/10.1080/1351847X.2021.1900887

Breemen, V. van, Fabozzi, F. J., & Vink, D. (2023). Intensified competition and the impact on credit ratings in the RMBS market. *Financial Markets, Institutions & Instruments, forthcoming.* https://doi.org/10.1111/fmii.12170

Chouliara, E., & Martino, E. D. (2021). *Risk retention in securitization and empty creditors* [Working paper]. EBI Working Paper Series No. 91. https://doi.org/10.2139/ssrn.3824733

Demiroglu, C., & James, C. (2012). How important is having skin in the game? Originator-sponsor affiliation and losses on mortgage-backed securities. *Review of Financial Studies*, *25*(11), 3217–3258. https://doi.org/10.2139/ssrn.1530231

Demyanyk, Y., & Van Hemert, O. (2009). Understanding the subprime mortgage crisis. *Review of Financial Studies*, *24*(6), 1848–1880. https://doi.org/10.1093/rfs/hhp033

European Banking Authority (EBA). (2014a). *Guidelines on significant credit risk transfer relating to Articles 243 and Article 244 of Regulation 575/2013* (EBA/GL/2014/05). https://www.eba.europa.eu/regulation-and-policy/securitisation-and-covered-bonds/guidelines-on-significant-risk-transfer-srt-for-securitisation-transactions

European Banking Authority (EBA). (2014b). *EBA report on securitization risk retention, due diligence and disclosure*. https://www.eba.europa.eu/sites/default/documents/files/documents/10180/534414/b152ba27-9a02-4d82-82a0-e05c8123a7df/Securitisation%20Risk%20Retention%20Report.pdf?retry=1

European Banking Authority (EBA). (2022). *EBA final draft regulatory technical standards* (EBA/RTS/2022/04). https://www.eba.europa.eu/sites/default/documents/files/document_library/Publications/Draft%20Technical%20Standards/2022/EBA-RTS-2022-04%20RTS%20on%20risk%20retention%20requirements%20for%20securitisations%20/1030491/Final%20Draft%20RTS%20on%20Risk%20Retention%20in%20securitisation.pdf

Fabozzi, F. J., van Breemen, V., Vink, D., Nawas, M., & Gengos, A. (2022). How much do investors rely on credit ratings: Empirical evidence from the U.S. and E.U. CLO primary market. *Journal of Financial Services Research, 2022* https://doi.org/10.1007/s10693-021-00372-x

Furfine, C. H. (2014). Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies*, *2*(2), 154–187. https://doi.org/10.1093/rcfs/cft008

Hibbeln, M. T., & Osterkamp, W. (2020). The impact of risk retention on the pricing of securitizations [Unpublished work]. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2112002

HM Treasury. (2021). *Review of the Securitisation Regulation: Report and call for evidence response. GOV.UK*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1040038/Securitisation_Regulation_Review.pdf

Hu, J., & Cantor, R. (2006). The relationship between issuance spreads and credit performance of Structured Finance Securities. *The Journal of Fixed Income*, *16*(1), 5–20. https://doi.org/10.3905/jfi.2006.640273

Kaptan, M. (2011). On the optimal design of risk retention in securitisation. *Risk Governance and Control: Financial Markets and Institutions*, *1*(3), 50–57. https://doi.org/10.22495/rgcv1i3art5

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2010). Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly Journal of Economics, 125*(1), 307–362. https://www.jstor.org/stable/40506283

Kiff, J., & Kisser, M. (2014). *A shot at regulating securitization. Journal of Financial Stability, 10*, 32–49. https://doi.org/10.1016/j.jfs.2013.02.003

Malekan, S., & Dionne, G. (2014). Securitization and optimal retention under moral hazard. *Journal of Mathematical Economics*, *55*, 74–85. https://doi.org/10.1016/j.jmateco.2014.10.003

Regulation (EU) No 462/2013 of the European Parliament and of the Council of 21 May 2013 amending Regulation (EC) No 1060/2009 on credit rating agencies. (2013). http://data.europa.eu/eli/reg/2013/462/oj

Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012, Article 405. (2013). http://data.europa.eu/eli/reg/2013/575/oj 288

Regulation (EU) No 2017/2402 of the European Parliament and of the Council of 12 December 2017 laying down a general framework for securitisation and creating a specific framework for simple, transparent and standardised securitisation. (2017). http://data.europa.eu/eli/reg/2017/2402/oj

Tavakoli, J. M. (2008). *Structured finance and collateralized debt obligations: New developments in cash and synthetic securitization* (2nd ed.). John Wiley & Sons.

Technical Committee of the International Organization of Securities Commissions. (2009). *Unregulated financial markets and products* [Final report]. International Organization of Securities Commissions. https://www.iosco.org/library/pubdocs/pdf/IOSCOPD301.pdf

Vanasco, V. (2017). The downside of asset screening for market liquidity. *The Journal of Finance*, *72*(5), 1937–1982. https://doi.org/10.1111/jofi.12519

Vink, D., Nawas, M., & van Breemen, V. (2021). Security design and credit rating risk in the CLO market. *Journal of International Financial Markets, Institutions and Money*, *72*, 101305. https://doi.org/10.1016/j.intfin.2021.101305

White, L. J. (2010). Markets: The credit rating agencies. *Journal of Economic Perspectives*, *24*(2), 211–226. https://doi.org/10.1257/jep.24.2.211

Chapter 7

General Discussion and Conclusion

7. General Discussion and Conclusion

The securitization market is most remembered for its role during the 2007-2009 Global Financial Crisis (GFC). Significant measures have been put in place in an attempt to better regulate this market since then, yet the effectiveness of these measures and what other effects they may have had are not always clear. In this dissertation, I look at the securitization market before, during, and after the GFC in order to study the most prevalent risks and provide several angles on how to optimize regulation. The overarching purpose is to provide new insights that may help regulators to optimize rules and regulations for the securitization market and help investors to make better informed decisions. I thereby try to further improve the securitization market and consequently the resilience of the financial system.

I do so by answering the following overarching research question:

> *To what extent do factors beyond credit ratings affect securities' credit quality, and to what extent do investors rely upon these ratings?*

To explore this question, I have investigated five empirical sub-questions, each of which is outlined in a separate chapter of this dissertation. The main findings and its interlinkages are discussed below to derive to the overarching outcome of this dissertation. Finally, the contribution, limitations of our study, and possible avenues for future research are provided.

7.1 Discussion

7.1.1 **Role of credit ratings**

In a perfect world, a credit rating reflects the full range of credit risks underlying a security. However, in practice there is a wide range of risks observed that do not (fully) seem to be incorporated in the securities' credit ratings.[85] Yet despite extensive criticism, CRAs continue to retain an important function as central entities in the financial markets. For instance, credit ratings are used in the prudential regulation of financial institutions and play a significant role in investment decisions of bond market participants. Any miscalculation of risks by CRAs can therefore have huge and painful consequences for regulators, investors, and also for the financial system as a whole, which was exemplified to a large extent during the global financial crisis. To avoid these events from happening in the future, CRAs are considerably more heavily regulated after the global financial crisis. In this dissertation, we have investigated how effective these rules and regulations are and if the market does indeed function better as a result.

We start by investigating the extent to which investors rely on credit ratings in pricing securities and show that they indeed do rely on ratings in determining their required yield. Interestingly, we observe a higher degree of reliance on credit ratings in the United States relative to the European market. However, in both markets investors still seem to rely on credit ratings attached to securities (see Chapter 2). This shows that ratings are still widely used and relied upon by investors to make investment decisions. As such, it is of the utmost importance that ratings adequately reflect the underlying credit risk of securities.

[85] As pointed out in Chapters 2 to 6 of this dissertation.

7.1.2 **Challenges in the securitization market**

Securitization literature univocally accentuate the undesirable consequences of the 'issuer pays' business model and 'winner-takes-most' fee models on the quality of credit ratings.[86] Despite the implementation of several rules and regulations to improve the market, these models are still in place and seem to have serious consequences for the quality of credit ratings. For example, our study shows that the complexity of a security's design is one of the elements that influence the rating shopping behavior of issuers and rating catering behavior of CRAs. We find that, even after the global financial crisis, issuers are likely to display rating shopping behavior for more complex securities. We also show that issuers tend to differentiate between CRAs when dealing with complex securities, e.g., they prefer a Moody's over an S&P rating (see Chapter 3). This suggests that issuers might favor the CRA (i.e., Moody's) that is willing to provide more optimistic ratings for deals that are engineered in a complex way. These findings suggest that the downside effects of the 'issuer pays' business model still seem to be present. In essence, when buying credit ratings, issuers seem to sagaciously seek to optimize their risk-return levels, rather than looking solely to the underlying credit quality of the security. The same is true when issuers construct a deal, they seem to construct more sizable transactions in lower risk environments (see Chapter 5).

In response to these downside effects, regulators have tried to improve the rating market by, amongst others, implementing rules and regulations that sought to stimulate the entrance of smaller and newer CRAs. Unfortunately, but in line with others [87], we show that a regulatory environment designed to encourage new CRAs to enter the market does not necessarily solve the problem of misleading credit ratings assigned by the prevailing market players. For example, we find that both

[86] See, e.g., He et al. (2016), Sangiorgi and Spatt (2017) and Zhou et al. (2017).
[87] See, e.g., Bae et al. (2019) and Becker and Milbourn (2011).

new (i.e., DBRS and KBRA) and incumbent (Moody's, S&P, and DBRS) CRAs adjust their credit ratings and their credit rating standards based on the competitive pressure of their peers. Our results also reveal that small CRAs (particularly KBRA) tend to inflate their ratings when dealing with more powerful issuers. Perhaps smaller CRAs use this as a strategy to win business from larger CRAs, as issuers with rating shopping tendencies prefer more optimistic ratings above others (see Chapter 4). This effect seems to be even stronger when they issue a rating for a security that is located in a lower-risk environment that comes with higher creditor protection (see Chapter 5).

The reason for issuers to be highly selective when choosing between ratings of different CRAs might also be related to inconsistencies of CRAs in (applying) rating methodologies. Interestingly, we observe these inconsistencies when assessing how different CRAs incorporate the level of creditor protection in their models to determine the credit ratings. We find that Moody's and DBRS do incorporate the level of creditor protection in their risk assessment while we find no such relation for KBRA, S&P and Fitch (see Chapter 5).

Altogether, issuer power enabled by the 'issuer pays' business model seems to influence the quality of credit ratings. At the same time, there also seems to be a risk for issuers and investors that CRAs use different, or an incomplete set of factors in their rating models when determining credit ratings.

7.1.3 **Investors' risk perspective**

Considering all the risks mentioned above, it is of utmost importance that investors are well-aware of these risks and price them accordingly. In our study, we show that investors indeed observe risks beyond credit ratings when pricing securities. For instance, we find that investors incorporate other security design factors (such as tranche count and CLO deal size) in their assessment of the funding cost for securities (see Chapter 2). Investors also seem to notice the inconsistencies between CRAs in their risk assessment. For example, they perceive more credit rating risk with Moody's compared to S&P, and as a result they seem to rely substantially less on a Moody's credit rating compared to S&P (see Chapter 3).

Investors also seem to be well aware of the power of issuers, particularly when dealing with large issuers or those with frequent issues. Proof of this is given in Chapters 2 and 4 where we show that both CRAs and investors are taking the power of issuers (in terms of size and frequency of issues) into account when rating and pricing securities.

Throughout our studies we use, amongst other things, the investors' risk perspective (i.e., primary issuance spread) to assess the efficiency and effectiveness of the current regulatory frameworks for the securitization market. We start by showing that the goal of regulatory bodies to move away from a sole reliance on credit ratings is only partially achieved. Investors still rely significantly on credit ratings, but they also price risks that they have observed beyond credit ratings (see Chapter 2). Subsequently, we argue that a regulatory environment that takes into account the complexity of a security's design may be more suited to regulate the market than one mainly looking at the number of credit ratings. We base this argument on our findings in Chapter 3 where we show that investors only require dual ratings for complex securitization deals. Finally, our findings strongly suggest that unlike regulation, investors differentiate between the different risk retention methods applied by the tranche retainer when pricing securities. The purpose of the rule is to force originators to hold a portion of skin-in-the-game with the aim to better align the interest between the originator and investor. However, to allow tranche retainers to cherry pick from different risk retention methods to determine how they hold a portion of the transaction, seems not fully aligned to this purpose (see Chapter 6). These conclusions show that parts of the current regulatory framework might be suboptimal and could benefit from revisions.

7.1.4 **The beauty of securitization**

One might argue that, in and of itself, the securitization technique is a beautiful tool for financial engineering that provides benefits to a country's financial system. The technique allows banks and other financial institutions to transform illiquid assets to tradable capital market instruments. This reduces the reliance on deposits and creates funding diversification which might result in lower financing cost for lenders such as banks. The solvency of banks could benefit from the enhanced liquidity and higher asset turnovers, thereby increasing their profitability. But not only banks benefit. Due to the efficiency gains of banks, it might result in lower financing cost for companies and other borrowers. It also provides benefits for investors, who can diversify their investment portfolio by not only investing in, e.g., government and corporate bonds but also in securitized assets (Kara et al., 2014). However, in order to sustainably profit from these benefits, it is necessary (based on the findings in this dissertation) to improve the (fine lines of the) current market structure and regulation.

7.2 Answering research questions

To summarize and answer the overarching research question, securities' credit quality is indeed affected by factors beyond the credit rating and while investors do still rely upon ratings, they also price risks that are perceived beyond it. Interestingly, we find that investors in both the US and EU market rely on credit ratings, but more so in the US market. Likewise, we find that investors in both markets take other security design factors beyond the credit rating into account when pricing securities, but again more so in the US market (first sub-question). Furthermore, we see that the complexity of a security's design has an impact on both rating shopping and rating catering behaviors of issuers (second sub-question). So apparently the credit rating is not only influenced by the securities' credit quality, as one might expect, but also used by market players as a means to expand market share and revenue. The same holds for the impact of CRA competition on rating quality, as both large and small CRAs seem to adjust their credit rating and rating standards based on competitive pressures of one another (third sub-question). Rating quality is also affected by the inconsistencies between CRAs in assigning credit ratings, particularly when it comes to the different levels of creditor protection (fourth sub-question). Finally, investors seem to price, beyond the credit rating, the risk of specific risk retention methods used by the originator. These results suggest that the regulatory methods in place to enforce retention do not equally align the interest of both the originator and investor (fifth sub-question).

Altogether, the results show that investors are exposed to credit rating risk, caused by several factors such as competition, rating shopping and catering behaviors, and inconsistencies between CRAs. However, investors do seem to be aware of some of these risks and price them accordingly, such as security design factors and differences between risk retention methods. The most important underlying cause for these shortcomings in the securitization market is the way in which the rating market is structured (i.e., the 'issuer pays' business model) and parts of the regulatory framework that seem suboptimal. In the next section we provide several concrete suggestions on how to improve the current market structure and regulation.

7.3 Contribution and Recommendations

7.3.1 **Prevention is better than cure:** Opportunities for regulators, policymakers, and supervisors

First and foremost, based on our findings, we recommend enforcing CRAs by regulation to change their core business model by moving from the 'issuer pays' business model towards the 'investor pays' business model. The latter refers to a business model where CRAs generate revenue by selling ratings to investors, instead of to issuers.[88] This would end the conflict of interest between the CRA and the issuer and thereby eliminating the negative effects of rating shopping and rating catering behaviors on the quality of ratings. If the investor were to be the key client of the CRA, one might assume that the CRA assigns a rating that solely reflects the underlying credit quality of a security, to align with the wishes of its client. While currently, the CRA acts in the interest of the issuer who might prefer the highest rating, even if this rating is inflated, as this will be beneficial for the issuer's own financial gains.

Secondly, but only if the above option is not considered to be realistic by the regulators, policymakers and supervisors for whatever reason, we recommend sharpening the disclosure requirements of CRAs and issuers, in particular for complex securities. Specifically, requiring CRAs to publish (preliminary) contacts between themselves and issuers and to comment on each other's rating. Such disclosure will help both issuers and investors to make better-informed decisions and include these considerations as they determine yield requirements. It might, for example reveal whether the CRAs are inclined to match each other's ratings

[88] Back in the days, CRAs made use of the 'investor pays' business model. In the late1960s and early 1970s, however, they changed this to the issuer pays business model. The change was due to the introduction of the high-speed photocopying machine in the 1960s that created fear amongst CRAs that it might negatively affect their business, as it allowed investors to easily replicate documents from one another (White, 2019).

(rating catering) or if the possibility of rating shopping behavior by issuers was present. These issues, however, would naturally disappear if CRAs operate under the 'investor pays' business model as per our primary suggestion.

Thirdly, the effectiveness of regulations could be improved if CRAs were also be required to publish specifically i) how rating standards have tightened or loosened over time (i.e., per segment of the securitization market), ii) prove how these changes in rating standards are detached from competitive pressure of their peers, and iii) how they have incorporated creditor protection in their risk assessment for credit ratings. This would enlighten investors on the train of thought and (changes in) methods used by CRAs and would help them to adapt their risk-pricing policies accordingly and on a timely basis. These suggestions to further improve information transparency through CRA disclosure do not have to be enforced by regulation per se but could also be pro-actively realized by CRAs themselves. Amongst others, this might help some of the skepticism on the reliability of credit ratings that some market participants might still have (see, e.g., Badoer et al., 2019).

Finally, we recommend regulators to re-evaluate whether the different regulatory risk retention methods should indeed be treated equally (as currently done by regulation). We show that the different methods do not seem to align to the interest of the originator and investors in an equal manner. Regulators might also seek to improve this, and the suggestions above, by trying to align the (diverging) legislative frameworks of the US and EU market on credit ratings.

7.3.2 **Cure in the meantime:** Opportunities for investors

For investors, we recommend that they inform their credit departments to hone their investment models according to the risks observed in this dissertation if they have not already done so. For example, by incorporating the risks that credit ratings may be influenced by competition among CRAs, and particularly the competition between the relatively new and more incumbent ones. Another factor to take into account is that rating shopping behavior of issuers is still influencing the quality of ratings, especially for securities with a complex design. Furthermore, the size of the issuer seems to matter and should be considered when one interprets the quality of a credit rating. Finally, investors should ideally perform their own risk assessment to determine the risks related to the level of creditor protection of securities, as some CRAs might not have (fully) incorporated this in their credit rating.

7.3.3 **Benefits for academic literature**

Our contribution to academic literature is manyfold and, to the best of our knowledge, we are the first to provide these insights. We are frontrunners in comparing investors in the US and EU CLO market with respect to the extent to which they rely on credit ratings in pricing securities. We are also the first to test the relation between the complexity of a CLO design and the number of ratings disclosed. Next, we explore the impact of increased competition in a market targeted heavily by regulation (RMBS market), where smaller CRAs have gained significant prominence after the global financial crisis. Furthermore, we are the first to link in-country differences in creditor protection related to the credit ratings attached to a security. Finally, we are the first to assess the impact of four different risk retention methods in the European RMBS market.

With that, our studies contribute to a growing body of literature on: credit ratings and credit spreads (e.g., Marques & Pinto, 2020; Yang et al., 2020), credit rating standards (see, e.g., Alp, 2013; Cafarelli, 2020), complexity of securitization transactions (see, e.g., Furfine, 2014; Skreta & Veldkamp, 2009), competition and rating quality (see, e.g., Badoer et al., 2019; Baghai & Becker, 2019; Bolton et al., 2012; Zhou et al., 2017), creditor rights (see, e.g., Bae & Goyal, 2009; Qian &

Strahan, 2007), and the effectiveness of risk retention methods (see, e.g., Bektić & Hachenberg, 2021; Malekan & Dionne, 2014).

7.4 Limitations and avenues for future research

"One thing I have learned in a long life: that all our science, measured against reality, is primitive and childlike -- and yet is the most precious thing we have"

– Albert Einstein

No research study is perfect and all studies have limitations. But limitations often reveal opportunities. Below we discuss the limitations of our studies and build upon them to suggest avenues for future research.

First, the limitation of our study and of prior empirical literature on rating shopping is that the underlying intention of an issuer to shop for credit ratings cannot be fully observed (Chapters 2 and 6). We can only assume by looking at the number of ratings that rating shopping was likely or not. It must be noted however, that the actual decision of the issuer remains unobservable for all those outside the originator's company. Academic literature would highly benefit if this information would become available (e.g., via stricter disclosure requirements).

Second, in assessing the impact of competition on rating quality (or misleading credit ratings), one might argue that our analyses might benefit from looking at default rates to confirm these results (Chapter 4). For example, the results would be even more substantiated if a credit rating labeled as 'misleading' would indeed have higher default rates than those *not* labeled as 'misleading'. I therefore suggest for future academic research to explore these relationships by looking at default rates over time, using secondary market data. In addition, one could scrutinize if investors price these risks accordingly.

Third, the time period used in our study on creditor protection could potentially be extended (Chapter 5). The current data has the limitation that, in this period, the majority of tranches that are originated and sold have exposure to California. Extending the dataset might result in a more widespread variation across states. The data also does not allow us to dig into the lowest granularity level to observe the exact portion of exposure to a specific state (so far data only allows to observe the most dominant exposure). If one can find such data, we highly suggest building upon and expanding our study by analyzing the impact of creditor protection across states. One might also decide to expand the geographical region to the European or the upcoming Chinese market while exploring these relations.

Fourth, future research could assess the inherent risk of the underlying pool of the securitization transactions while performing similar studies as provided in this dissertation. Data limitations in our studies hindered statistical control for the inherent risk of the underlying pool. For example, one could assess, using loan-level data, how the inherent risk of the underlying pool relates to the creditor protection differences across states (Chapter 5) or the chosen risk retention method by tranche retainers (Chapter 6).

Finally, our study includes a very diverse set of pricing dynamics (Chapters 2, 3 and 5), but naturally these are not all encompassing. Therefore, for further academic work we suggest that for the EU market in particular, there is need to improve investors understanding of the pricing dynamics related to securities. Academic research might also benefit from more comprehensive analyses on the potential divergence in approach between the investor community in the US and EU market.

References

Alp, A. (2013). Structural shifts in credit rating standards. *The Journal of Finance*, *68*(6), 2435–2470. https://doi.org/10.1111/jofi.12070

Badoer, D. C., Demiroglu, C., & James, C. M. (2019). Ratings quality and borrowing choice. *Journal of Finance, 74*(5), 2619-2665. https://doi.org/10.1111/jofi.12820

Bae, K. H., Driss, H., & Roberts, G. S. (2019). Does competition affect ratings quality? Evidence from Canadian corporate bonds. *Journal of Corporate Finance, 58*, 605–623. https://doi.org/10.1016/j.jcorpfin.2019.07.009

Bae, K., & Goyal, V. K. (2009). Creditor rights, enforcement, and bank loans. *The Journal of Finance*, *64*(2), 823–860. https://doi.org/10.1111/j.1540-6261.2009.01450.x

Baghai, R. P., & Becker, B. (2020). Reputations and credit ratings: Evidence from commercial mortgage-backed securities. *Journal of Financial Economics, 135*(2), 425–444. https://doi.org/10.1016/j.jfineco.2019.06.001

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, *101*(3), 493–514. https://doi.org/10.1016/j.jfineco.2011.03.012

Bektić, D. & Hachenberg, B. (2021). European arbitrage CLOs and risk retention. *European Journal of Finance 27*(18), 1791-1803. https://doi.org/10.1080/1351847X.2021.1900887

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance, 67*(1), 85–111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Cafarelli, A. (2020). Creditworthiness risk over years: The evolution of credit rating standards. *Journal of Corporate Accounting & Finance*, *31*(4), 48–59. https://doi.org/10.1002/jcaf.22461

Furfine, C. H. (2014). Complexity and loan performance: Evidence from the securitization of commercial mortgages. *The Review of Corporate Finance Studies*, *2*(2), 154–187. https://doi.org/10.1093/rcfs/cft008

He, J. J., Qian, J. Q. J., & Strahan, P. E. (2016). Does the market understand rating shopping? Predicting MBS losses with initial yields. *Review of Financial Studies*, *29*(2), 457–485. https://doi.org/10.1093/rfs/hhv067

Kara, A., Ozkan A., & Altunbas, Y. (2014). Securitisation and bank risk: What do we know so far? *Review of Behavioral Finance, 8*(1), 2–16. https://doi.org/10.1108/RBF-07-2014-0039

Malekan, S., & Dionne, G. (2014). Securitization and optimal retention under moral hazard. *Journal of Mathematical Economics*, *55*, 74–85. https://doi.org/10.1016/j.jmateco.2014.10.003

Marques, M. O., & Pinto, J. M. (2020). A comparative analysis of ex ante credit spreads: Structured finance versus straight debt finance. *Journal of Corporate Finance*, *62*, 101580. https://doi.org/10.1016/j.jcorpfin.2020.101580

Qian, J., & Strahan, P. E. (2007). How laws and institutions shape financial contracts: The case of bank loans. *The Journal of Finance*, *62*(6), 2803–2834. https://doi.org/10.1111/j.1540-6261.2007.01293.x

Sangiorgi, F., & Spatt, C. (2017). Opacity, credit rating shopping, and bias. *Management Science*, *63*(12), 4016–4036. https://doi.org/10.1287/mnsc.2016.2558

Skreta, V., & Veldkamp, L. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, *56*(5), 678–695. https://doi.org/10.1016/j.jmoneco.2009.04.006

White, L. (2019). The credit rating agencies and their role in the financial system. In E. Brousseau, J. M. Glachant & J. Sgard (Eds.), *Oxford handbook on institutions, international economic governance, and market regulation*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190900571.001.0001

Yang, L., Wang, R., Chen, Z., & Luo, X. (2020). What determines the issue price of lease asset-backed securities in China? *International Review of Financial Analysis*, *72*, 101583. https://doi.org/10.1016/j.irfa.2020.101583

Zhuo, X., Xu, G., & Wang, Y. (2017). The issuer-pays business model and competitive rating market: Rating network structure. *The Journal of Real Estate Finance and Economics*, *55*(2), 216–241. https://doi.org/10.1007/s11146-016-9563-2

Chapter 8

Summary
(English & Dutch)

8.1 Summary (English)

Chapter 1: *General introduction*

In **Chapter 1**, we introduce the main concepts and theories used in our research and list the research questions that we seek to answer in this dissertation. Our study revolves around securitization in the United States (US) and European Union (EU) market. Securitization is the process in which various types of loans are bundled together and structured into tradable securities which are sold to investors. The securitization is divided into several tranches, each with a different credit quality, as denoted by the credit rating assigned by credit rating agencies (CRAs). Throughout this dissertation, we seek to answer the question to what extent factors beyond credit ratings affect securities' credit quality and we are also interested to what extent investors rely upon these credit ratings. To explore this, we have established five empirical sub-questions, of which each question is answered in a separate chapter of this dissertation (Chapters 2 to 6). In Chapter 7, we conclude by answering the overarching research question and describe the contributions and limitations of our studies, including recommendations for future research.

In our studies, we analyze the securitization market by using pooled cross-sectional data of tranches at issuance and applying several ordinary least square (OLS) and (ordered) logit regression models.

Chapter 2: *How much do investors rely on credit ratings: Empirical evidence from the US and EU CLO primary market*

In **Chapter 2**, we start by investigating the extent to which investors rely on credit ratings and other factors beyond credit ratings in determining the funding cost for collateralized loan obligation (CLO) tranches in the period 1997-2015.

The results show that investors do rely considerably on credit ratings in pricing CLOs and that a large divergence exists between investors' reliance in the US and EU market. Namely, the reliance on credit ratings is stronger in the US than the EU market. Investors also incorporate other security design factors (such as tranche count and CLO deal size) in their assessment of the funding costs for CLO tranches. Investors in the US market do so to a greater extent than investors in the EU. The results also show that, after the global financial crisis, the reliance on credit ratings remained more or less stable in the US but dropped significantly in the EU market. Hence, the level of reliance is more consistent over time in the US than in the EU market. In addition, our results show that only investors in the EU market take issuer size into account when pricing CLO tranches. Specifically, they increase their reliance on credit ratings and other factors in case of smaller or infrequent issuers. In addition, the study demonstrates that tightening and loosening of credit rating standards by CRAs adversely impacts funding cost of CLOs. This effect is stronger for the US market, where investors seem to price CLOs tighter when credit standards loosen.

Chapter 3: *Security design and credit rating risk in the CLO market*

In **Chapter 3**, we study the extent to which complexity of a security's design impacts rating shopping and rating catering for CLO tranches in the period 1996-2013. The results show that complexity of a security's design indeed impacts rating shopping and rating catering behaviors in the CLO market and that this behavior is different before and after the global financial crisis. We find that prior to the global financial crisis, CLOs with complexity characteristics were more likely to have dual credit ratings than a single credit rating. This suggests that complex CLOs deals are less likely to have been subject to rating shopping but rather been subject to rating catering. However, in the post-crisis period, we find that complex CLOs were more likely to have one disclosed rating instead of two (i.e., higher likelihood of rating shopping). Overall, we show that complexity matters in the decision of issuers to report one or two credit ratings for CLO tranches. Finally, the results show that investors vary in their required yield based on CRA risk assessments. For tranches rated by S&P, investors do not significantly rely on the additional information content of a rating by Moody's in their pricing. We conclude that there is credit rating risk for investors as the credit rating might not fully or accurately reflect the actual credit risk.

Chapter 4: *Intensified competition and the impact on credit ratings in the RMBS market*

In **Chapter 4**, we investigate the extent to which competition between large and small CRAs has an impact on the quality of credit ratings and credit rating standards. We analyze the competition between CRAs in the residential mortgage-backed securities (RMBS) market for the period 2017-2020. The results show that both small and large CRAs adjust their credit ratings based on competitive pressures of their peers. In this study, we use DBRS and KBRA as representatives of small CRAs and Moody's, S&P, and Fitch as the large, global CRAs. This study also shows that when competitive pressure increases, both large and small CRAs tend to adjust their rating standards. Finally, the results reveal that small CRAs (especially KBRA) tend to inflate their ratings, on average, when dealing with more powerful issuers. These results indicate that CRAs not only consider underlying credit risk factors when assigning a credit rating to RMBS tranches but also use ratings to expand market share and revenue.

Chapter 5: *The impact of creditor protection in US states on the RMBS market*

In **Chapter 5**, we investigate the extent to which CRAs provide consistent and reliable credit ratings given the different levels of creditor protection across US States. We use data on RMBS tranches that are originated and sold in the US market between 2017-2020. The results show that Moody's and DBRS report lower (higher) credit ratings for tranches issued in states with lower (higher) creditor protection. However, for KBRA, S&P, and Fitch we find no significant relationship. We also show that new CRAs (DBRS and KBRA) are more likely to provide a more optimistic rating compared to incumbent CRAs when the tranche's collateral is located in a state with a low creditor protection. Finally, we find that issuers construct and sell deals with larger transaction values in more creditor friendly states. These results indicate that one should wisely interpret the quality of credit ratings when it comes to the level of creditor protection.

Chapter 6: *Should all skin-in-the-game methods be treated equally? Evidence from the European securitization market*

In **Chapter 6**, we investigate the extent to which the different regulatory risk retention methods have an impact on the pricing and ratings of European securitization tranches between 2011 and 2021. As of 2011, European regulation requires the originator to retain a significant portion of so-called skin-in-the game, to better align the interest between the investor and originator. According to the regulation, the tranche retainer is allowed to select one of the prespecified retention methods to hold skin-in-the-game. While all methods are treated equally by regulation, our results show that investors and CRAs do not value the different risk retention methods in an equal manner. For example, taking the first loss tranche method as the base case, we find that investors reduce the spread at issuance when the tranche retainer has applied the vertical slice or on-balance sheet method. We also find that CRAs experience more rating disagreements for the first loss tranche method. The results indicate that – although the risk retention rules set forth a minimum level of skin-in-the-game – a full alignment of interest between issuers and investors does not necessarily seem to have been attained by allowing the tranche retainer to cherry pick between different methods.

Chapter 7: *General discussion & conclusion*

In **Chapter 7**, we conclude by discussing the main findings and answer the central research question. We conclude that credit ratings are indeed affected by factors beyond the securities' credit quality, such as i) competition and rating shopping behaviors, ii) regulatory deficiencies, and iii) inconsistencies between the credit ratings of different CRAs. Furthermore, we show that investors do rely on credit ratings (particular in the US market), but they also seem to be aware of (some of the) credit rating risks and price them accordingly. Our findings might be relevant to regulators, policymakers, supervisors and investors. Based on our results, we recommend to ideally enforce CRAs to change their core business model towards the 'investor pays' business model. We also provide concrete recommendations on how to improve the disclosure requirements of CRAs and we recommend re-evaluating the different regulatory risk retention methods. We conclude by listing the limitations of our studies and provide avenues for possible future research.

8.2 Samenvatting (Dutch summary)

Hoofdstuk 1: *Algemene introductie*

In **hoofdstuk 1** introduceren we de belangrijkste concepten en theorieën die centraal staan in dit onderzoek en benoemen we onze onderzoeksvragen. We hebben vijf sub-onderzoeksvragen gedefinieerd die separaat worden beantwoord in de hoofdstukken 2 t/m 6. Tenslotte geven we in hoofdstuk 7 een samenvatting van de belangrijkste bevindingen, beantwoorden we de hoofdonderzoeksvraag, en reflecteren we op de sterke en zwakke punten van ons onderzoek.

Ons onderzoek richt zich op de securitisaties die worden uitgegeven in de Amerikaanse en Europese markt. Een securitisatie is een verzamelnaam voor de techniek om niet-verhandelbare financiële activa om te zetten in verhandelbare gestructureerde obligaties. Een securitisatie bestaat uit verschillende tranches met elk een ander risicoprofiel en winstmarge. Het risicoprofiel van een securitisatie wordt weergegeven door een kredietbeoordeling die wordt opgesteld door een kredietbeoordelingsbureau. De hoofdonderzoeksvraag die we beantwoorden in dit onderzoek is in hoeverre verschillende factoren, buiten de kredietbeoordeling om, impact hebben op de kredietwaardigheid van securitisaties. Daarnaast onderzoeken we in hoeverre beleggers vertrouwen op een kredietbeoordeling. In dit onderzoek maken we gebruik van cross-sectionele data van securitisatie tranches op de dag van uitgave. We analyseren de data door middel van verschillende meervoudige lineaire en (ordinale) logistische regressiemodellen.

Hoofdstuk 2: *How much do investors rely on credit ratings: Empirical evidence from the US and EU CLO primary market*

In **hoofdstuk 2** onderzoeken we de mate waarin beleggers vertrouwen op de kredietbeoordeling en welke additionele factoren zij meenemen in het bepalen van hun risicopremie. In deze studie analyseren we *collateralized loan obligation (CLO)* tranches die zijn uitgegeven en verkocht tussen 1997 en 2015. De resultaten laten zien dat beleggers inderdaad in belangrijke mate vertrouwen op de kredietbeoordeling in het bepalen van hun risicopremie. Maar we constateren ook dat er significante verschillen zijn tussen beleggers in de Amerikaanse markt en die in de Europese markt. Zo is het vertrouwen in de kredietbeoordeling sterker bij de Amerikaanse belegger. Daarnaast laten de resultaten zien dat beleggers additionele factoren meenemen in hun risicopremie, boven op de kredietbeoordeling, bijvoorbeeld de design factoren van de securitisatie (zoals het aantal tranches en de grootte van een deal). Ook hier vertrouwen Amerikaanse beleggers meer op design factoren dan de Europese beleggers. Na de mondiale financiële crisis is het vertrouwen van Amerikaanse beleggers in kredietbeoordelingen min of meer stabiel gebleven, terwijl het vertrouwen van Europese beleggers aanzienlijk is gedaald na de crisis. Het vertrouwen van Amerikaanse beleggers is dus stabieler over tijd dan het vertrouwen van Europese beleggers. Tevens laten de resultaten zien dat alleen Europese beleggers rekening houden met de grootte van de obligatie uitgever in het bepalen van hun risicopremie voor CLO tranches; het vertrouwen is groter in het geval van een kleine obligatie uitgever. Ten slotte laat de studie zien dat het aanscherpen en versoepelen van kredietstandaarden van kredietbeoordelingsbureaus een inverse relatie heeft met de risicopremie van CLOs. Dit is met name het geval in de Amerikaanse markt, waar beleggers een hogere prijs vragen wanneer kredietstandaarden worden versoepeld.

Hoofdstuk 3: *Security design and credit rating risk in the CLO market*

In **hoofdstuk 3** onderzoeken we de mate waarin de complexiteit van een securitisatie design impact heeft op *rating shopping* en *rating catering* gedrag. We analyseren CLO tranches die zijn uitgegeven en verkocht tussen 1996 en 2013. Allereerst laten de resultaten zien dat de complexiteit van een securitisatie design inderdaad *rating shopping* en *catering* gedrag beïnvloedt en dat er verschil zit tussen dergelijk gedrag voor- en na de financiële crisis. Voor de financiële crisis was de kans groter dat complexere CLOs twee kredietbeoordelingen hadden dan één kredietbeoordeling. Deze resultaten suggereren dat complexe CLO tranches in hogere mate blootstaan aan *rating catering* gedrag en in mindere mate aan *rating shopping* gedrag. Na de financiële crisis, is er een verhoogde kans dat complexe CLO tranches één kredietbeoordeling hebben in plaats van twee (oftewel, meer kans op rating shopping gedrag). Tenslotte laten de resultaten zien dat beleggers hun risicopremie van CLO tranches aanpassen op basis van de kredietbeoordelaar. Zo laten we bijvoorbeeld zien dat wanneer een CLO beoordeeld is door S&P, beleggers geen additionele informatie halen uit een extra kredietbeoordeling van Moody's. Samengevat laten de resultaten zien dat complexiteit belangrijk is bij het besluit van obligatie uitgevers om één of twee kredietbeoordelingen te geven voor CLO tranches. We concluderen dat er voor beleggers extra kredietrisico's zijn die niet accuraat of volledig worden weergegeven in een kredietbeoordeling.

Hoofdstuk 4: *Intensified competition and the impact on credit ratings in the RMBS market*

In **hoofdstuk 4** onderzoeken we hoe de kwaliteit van kredietbeoordelingen en kredietstandaarden wordt beïnvloed door de concurrentie tussen kleine en grote kredietbeoordelingsbureaus. We classificeren DBRS en KBRA als vertegenwoordigers van de kleine kredietbeoordelaars en Moody's, S&P, en Fitch als de wereldwijd grotere spelers. We onderzoeken de concurrentie tussen kredietbeoordelingsbureaus voor de residential mortgage-backed securities (RMBS) markt tussen 2017 en 2020. De resultaten laten zien dat zowel kleine als grote kredietbeoordelaars hun kredietbeoordeling aanpassen wanneer er meer concurrentie is. Ook laten we zien dat bij verhoogde concurrentie, zowel kleine als grote kredietbeoordelaars hun kredietstandaarden aanpassen. Tenslotte laten de resultaten zien dat kleine kredietbeoordelaars (specifiek KBRA) hun kredietbeoordelingen verhogen wanneer de transactie is uitgegeven door een grote (invloedrijke) uitgever. Op basis van deze studie concluderen we dat kredietbeoordelaars niet enkel kijken naar kredietrisicofactoren wanneer zij een kredietbeoordeling uitgeven voor RMBS tranches, maar kredietbeoordelingen ook gebruiken om hun marktaandeel en winsten te vergroten.

Hoofdstuk 5: *The impact of creditor protection in US states on the RMBS market*

In **hoofdstuk 5** wordt er ingezoomd op de mate waarin kredietbeoordelaars consistente en betrouwbare kredietbeoordelingen uitgeven, ondanks het verschil in debiteursbescherming tussen Amerikaanse staten. Om dit te onderzoeken gebruiken we data van RMBS tranches die zijn uitgegeven en verkocht in de Amerikaanse markt tussen 2017 en 2020. De resultaten laten zien dat Moody's en DBRS slechtere kredietbeoordelingen rapporteren voor RMBS tranches die zijn uitgegeven in staten met slechtere debiteursbescherming. We vinden geen significante relatie voor KBRA, S&P en Fitch. Wel laten we zien dat de kans groter is dat een relatief nieuwe kredietbeoordelaar (DBRS en KBRA) een optimistischere kredietbeoordeling uitgeeft dan een gerenommeerde partij (Moody's, S&P en Fitch), wanneer het onderpand van de transactie zich bevindt in een staat met slechtere debiteursbescherming. Als laatste laten we zien dat uitgevers geneigd zijn om transacties met grotere transactiewaardes uit te geven in staten met betere debiteursbescherming. Op basis van deze resultaten concluderen we dat de mate van debiteursbescherming in verschillende staten invloed kan hebben op de kwaliteit van de kredietbeoordeling.

Hoofdstuk 6: *Should all skin-in-the-game methods be treated equally? Evidence from the European securitization market*

In **hoofdstuk 6** onderzoeken we de mate waarin de verschillende *risk retention* methodes invloed hebben op de prijs, structuur en kredietbeoordeling van

Europese securitisatie tranches in de periode tussen 2011 en 2021. Sinds 2011 vereist Europese wet- en regelgeving dat een uitgever van securitisatie tranches een significant deel van de securitisatie op eigen balans moet houden, zogeheten *skin-in-the-game*. Het doel van deze regel is om de belangenverstrengeling tussen beleggers en uitgevers te verminderen. De uitgever krijgt de optie om uit één van de vijf voorgeschreven methodes te kiezen om *skin-in-the-game* te houden. Terwijl alle methodes op gelijke risicovoet worden gezet door wet- en regelgeving, laten wij zien dat zowel beleggers, uitgevers als kredietbeoordelaars verschillende risicoprofielen toekennen aan de verschillende methodes. Onze resultaten laten bijvoorbeeld zien dat beleggers hun risicopremie verlagen voor transacties met de *vertical slice* of *on-balance sheet* methode, ten opzichte van de *first loss tranche* methode. Ook geven de resultaten weer dat kredietbeoordelaars meer moeite hebben met het bepalen van een kredietbeoordeling voor transacties met de *first loss tranche* methode. Wij concluderen dat, ondanks het wettelijk minimumniveau van *skin-in-the-game* door uitgevers, de belangenverstrengeling tussen de belegger en uitgever niet (volledig) wordt opgelost doordat de uitgever kan kiezen uit verschillende *risk retention* methodes.

Hoofdstuk 7: *Algemene discussie & conclusie*

In **hoofdstuk 7** vatten we de belangrijkste bevindingen van onze studie samen en beantwoorden we de hoofdonderzoeksvraag. We concluderen dat krediet-beoordelingen niet alleen worden beïnvloed door het kredietrisico van de se-curitisatie-transactie, maar ook door andere factoren. Als voorbeeld door i) marktconcurrentie en rating shopping gedrag, ii) tekortkomingen in wet- en regelgeving, en iii) inconsistenties tussen de kredietbeoordelingen van verschil-lende kredietbeoordelaars. Ook laat onze studie zien dat beleggers vertrouwen op de kredietbeoordeling (met name in de Amerikaanse markt), maar dat zij zich ook (deels) bewust zijn van additionele risico's. Onze bevindingen zijn rel-evant voor regelgevers, beleidsmakers, toezichthouders en beleggers. Op basis van onze resultaten adviseren wij dat kredietbeoordelaars idealiter hun bedrijfsmodel veranderen naar het '*investor pays*' bedrijfsmodel. Ook geven we concrete aanbevelingen om de openbaarmakingsvereisten van kredietbeoordelaars te verbeteren. Daarnaast raden wij aan om het wettelijk kader omtrent de *risk retention* regels te herzien. We sluiten af met het benoemen van de beperkingen van onze studie en geven een aantal aanbevelingen voor toekomstig onderzoek.

Publications

Dissemination of Chapters

Chapters 2 to 6 are based on five stand-alone papers. These papers have been published as central bank working papers and/or in highly ranked peer reviewed journals. They have also been presented at several (international) research conferences and seminars. The dissemination of the chapters is as follows:

Chapter 2

- ✓ *Published in the Journal of Financial Services Research*

Chapter 3

- ✓ *Published in the Journal of International Financial Markets, Institutions & Money*
- ✓ *Published in De Nederlandsche Bank Working Paper Series*
- ✓ *Presented at American Finance Association Conference 2020 in San Diego*
- ✓ *Presented at Paris Financial Management Conference 2019 in Paris*
- ✓ *Presented at De Nederlandsche Bank Research Seminar*
- ✓ *Presented at Nyenrode Brown Bag 2020*

Chapter 4

- ✓ *Published in Financial Markets, Institutions & Instruments*
- ✓ *Published in European Central Bank Working Paper Series*
- ✓ *Presented at American Finance Association Conference 2022 (virtual)*
- ✓ *Presented at Nyenrode Brown Bag 2022*

Chapter 5

- ✓ *Presented at Annual Workshop of ESCB Research Cluster 3 2022 in Lisbon*
- ✓ *Presented at European Central Bank Research Seminar*
- ✓ *Submitted to Financial Markets, Institutions & Instruments*

Chapter 6

- ✓ *Presented at European Central Bank Research Seminar*
- ✓ *Presented at the Central Bank Research Association (CEBRA) Annual Meeting 2023 in New York*
- ✓ *Submitted to the European Central Bank Working Paper Series*

List of Publications

Academic publications

Breemen, V. van, Fabozzi, F. J., Nawas, M. & Vink, D. (2023). The impact of creditor protection in US states on the RMBS market. *Financial Markets, Institutions & Instruments*, currently under review.

Breemen, V. van, Fabozzi, F. J., & Vink, D. (2022). *Intensified competition and the impact on credit ratings in the RMBS market* [Working paper]. ECB Working Paper No. 2691. https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2691~e4306089a4.en.pdf

Breemen, V. van, Fabozzi, F. J., & Vink, D. (2023). Intensified competition and the impact on credit ratings in the RMBS market. *Financial Markets, Institutions & Instruments, 32*(2), 51-86. https://doi.org/10.1111/fmii.12170

Breemen, V. van, Schwarz, C. & Vink, D. (2023). *Risk retention in the European securitization market: skimmed by skin-in-the-game methods* [Working paper]. ECB Working Paper, currently under review.

Fabozzi, F. J., Breemen, V. van, Vink, D., Nawas, M., & Gengos, A. (2022). How much do investors rely on credit ratings: Empirical evidence from the U.S. and E.U. CLO primary market. *Journal of Financial Services Research, 63*, 221-247. https://doi.org/10.1007/s10693-021-00372-x

Vink, D., Nawas, M., & Breemen, V. van (2021). Security design and credit rating risk in the CLO market. *Journal of International Financial Markets, Institutions and Money*, *72*, 101305. https://doi.org/10.1016/j.intfin.2021.101305

Vink, D., Nawas, M., & Breemen, V. van (2021). *Security design and credit rating risk in the CLO market* [Working paper]. DNB Working Paper No. 643. https://www.dnb.nl/media/c4mojusj/working-paper-no-643.pdf

Other publications

Breemen, V. van & Vink, D. (2023). *Contributing to global financial stability: Dedicated research on risks in the capital market* (Impact Case May 2023). Nyenrode Business Universiteit. https://www.nyenrode.nl/nieuws/n/een-bedreiging-voor-financi%C3%ABle-stabiliteit--risico-s-in-de-kapitaalmarkt

Nawas, M., Vink, D., & Breemen, V. van (2020). IFRS-9 kan economisch herstel in de weg zitten. In L. Paape, C. Hilhorst, B. Jansen, B. van der Linden, & C. de Roover (Eds.), *COVID-19: een bevel uit het niets* (pp. 159-173). Mediawerf Uitgevers.

About the Author

Curriculum Vitae

Vivian Marit van Breemen (26-05-1993) was born on a boat in the Zaan area and raised on her parents' superyacht shipyard in Makkum, the Netherlands. Growing up, Vivian spent most of her time on the back of a horse. She finished secondary education at RSG Magister Alvinus Sneek in 2010. Straight afterwards she started studying International Business Management at Stenden University Leeuwarden. As part of her Bachelor of Applied Science, she did an exchange semester in Doha, Qatar. Her love for the academic world started during her Pre-Master and Master of Science in International Business and Economics at the University of Groningen. During her master, she participated in the International Business Research (IBR) program of the University of Groningen. As part of this program, she worked for Heineken in Jakarta, Indonesia. After graduating from the University of Groningen in 2016, she decided to move to Breukelen to obtain her second master's degree in Financial Management at Nyenrode Business Universiteit.

In 2018, at the age of 24, she started her first grown-up job as supervisor at De Nederlandsche Bank (DNB) in Amsterdam. She focused on credit and climate-related risks to which financial institutions are exposed. In 2020, she was selected to participate in DNB's high potential program with a focus on future leadership. Next to her full-time job as supervisor, she commenced work on her PhD supervised by Professor D. Vink at Nyenrode Business University. This research was focused on credit rating risks in the securitization market. During her part-time PhD studies, she got the opportunity to attend several international research conferences and to supervise several students in writing their master thesis. At the beginning of 2022, she took on a new position as supervisor at the European Central Bank (ECB) in Frankfurt, Germany. She is currently in the ECB's Supervisory Strategy and Risk directorate working on numerous strategic projects related to banking risks.

Acknowledgement

Acknowledgement

The completion of this dissertation would not have been possible without all the special and important people in my life.

My most profound appreciation goes to my promotor, ***Professor Dennis Vink***. Thank you for your unwavering support and belief in me. Your enthusiasm, optimism, and ability to motivate others around you have been extremely important to me. You have pushed me to go beyond my own boundaries to consistently get the most out of myself. I will never forget the many evenings with long phone calls discussing research and the amount of effort you have put into guiding me. Your immense research knowledge and plentiful experience have encouraged me in all times. You have been an amazing teacher. Thank you for everything.

I would like to express my sincere gratitude to ***dr. Mike Nawas***. Together with Dennis you have spent countless hours supporting and guiding me throughout my PhD, without which my experience would have been vastly different. Your guidance and support have always been extremely valuable to me. Your incredible wisdom and wealth of practical experience set an amazing example which I look to follow.

Furthermore, I would like to extend my sincere gratitude to ***Professor Frank J. Fabozz***i. It has been an honor working with you. Thank you for all the advice and guidance on my research. Your level of seniority, position in the academic world as well as the content of your work has greatly inspired me during my research.

Dear members of the examination committee, ***Prof dr. Arnoud W. A. Boot, Prof dr. Jakob de Haan***, ***Prof dr. Ivo Arnold*** and ***Prof dr. Ruud G. A. Vergoossen***, thank you so much for the time and effort that you have put into assessing this dissertation. I am very much looking forward to discussing my research with you.

Dear ***Professor Jakob de Haan***, thank you for supporting my research proposal and the publication of my work in the DNB Working Paper Series.

To all co-authors. Thank you for your valuable input, without which this dissertation would not have been the same. Dear ***Austin Gengos***, thank you for your contribution and the fine bottle of champagne that you sent as a gesture of your appreciation, it is greatly appreciated.

I would like to thank De Nederlandsche Bank (DNB) for being such an amazing employer. In particular, I would like to offer my special thanks to my manager, ***Marloes Tijbout***, and the NATIN management team led by ***Pieter-Reinier Maat***. The opportunities that you have offered me are tremendous. Thank you for providing all the resources that have helped me to successfully complete this dissertation. Thank you for allowing me to participate in DNB's high potential program and for providing me the opportunity to do a secondment at the European Central Bank (ECB).

Dear Marloes, beyond all this, I would like to thank you for being the best manager I will ever have and for all your guidance in both my work and private life (such as holiday recommendations in Dubai).

To all NATIN colleagues and especially the BPA team. Thank you for making DNB feel like home!

A special thanks to ***Max Simonis***. Max, you are amazing. I very much appreciate you for guiding me in my work and for all the joyful moments that we had. Also, many thanks for reviewing sections of this book.

Dear ***Hendrik Jan Boehlé***, thank you for all the opportunities that you have offered me in support of my research and professional development.

I would like to thank all my colleagues at the ECB. It has been a pleasure working with all of you. A special thanks to ***dr. Claudia Schwarz*** and ***dr. Klaus Düllmann*** for all their guidance and support on my work and allowing me to attend several international conferences. Dear Claudia, thank you for making me feel at home at the ECB. Your guidance and enthusiasm have been very valuable in forming one of the chapters of this dissertation.

I would also like to thank my colleagues in the Strategic Risk and Analytics team for assisting in data collection and all the inspiring research sessions that we have had. Special thanks to ***Christopher Scheins*** for helping me with my research while at the ECB and for being such a good office-roommate.

I would like to thank ***Laurène Jammes-Floreani*** for being my friend and making my time in Frankfurt truly rewarding.

To my fellow PhD buddy, ***Robin Edelbroek***, thank you for exchanging PhD experiences. It was very enlightening to hear that most of my frustrations were fully justified.

My beloved paranymphs and close friends, ***Evelyn Boot*** and ***Emilien Wegerif***. Thank you so much for supporting me throughout my PhD but particularly for (literally) standing behind me while I take my final steps in this journey. Eef, thank you for always being there for me and for being such an honest friend. Your enthusiasm makes everything brighter and your graciousness is truly amazing. Eem, thank you for being this crazy doctor friend who I can always count on (mostly for all but medical stuff). You are an amazing friend and always make me laugh!

To all the members of my sorority, Volante. I am proud to be part of this strong and powerful group of women. Thank you for all the close connections and friendships that you have given me.

Dear ***Lara van Bueren***, thank you for being my most organized and attentive friend. You are super important to me, I really value all the great moments that we have had so far!

I would like to thank ***Lotte Cloostermans*** for being my friend and for all the inspirational talks we have had over wine. Your passion and ability to listen (and advise) is amazing.

To my friend ***Kyra Mulder***, thank you for the thrilling adventures we had while travelling through Asia and all those afterwards. May there be many more!

To my friends ***Michelle den Ouden*** and ***Ezgim Yucel***. Ladies, you were the most amazing roomies I could have ever wished for at the Nyenrode campus. Our regular lunches and drinks give me a lot of joy and inspiration!

To my oldest friend, ***Nikki Koornstra***, the connection we have feels eternal and I am so grateful to have you by my side for the past 26 (!) years.

I would like to thank all my other friends and my family for supporting me in any kind of way. In particular my uncle, ***Hans Mulder***, for having me as his paranymph.

To my sis in law, ***Annie Sie Wan Wong***. I admire you for being such a strong woman. Thank you for proofreading my articles and for sharing all your own PhD experiences. I am so grateful to have you as my sis in law.

To the best brother in the world, ***Jorden van Breemen***. You are more than I could have ever wished for. Thank you for always being there for me and for the funny jokes and languages that only we share. Blood is thicker than water!

I owe most of my thanks to my parents, ***Nico*** and ***Marjan van Breemen***. Pap, mam, thank you for standing behind me no matter what. Combining my PhD with a full-time job would have never been possible without the amazing stability you have offered me throughout this journey and throughout my life. Thank you for leading by example, you have nailed your jobs as parents and as super yacht builders, which will always inspire me. Thank you for all the special life experiences you have given me and for all the sacrifices you have made in preparing me for the future. Mostly thank you for your infinite love and warmth. This dissertation is dedicated to you.
I love you!

To the love of my life, ***Raoul de Mos***. Dear lifey, thank you for the many hours you have listened to me talking about my PhD and for proofreading hundreds of pages of this book. Your advice has been truly rewarding. I admire your intrinsic motivation in life and am super proud of all you have achieved already. Thank you for supporting me in pursuing my dreams and for having many dreams together with me. I am extremely excited to spend the rest of my life with you and to discover all the beautiful things that life has to offer, together with you. Wherever the wind may blow us.

AAA

NYENRODE
BUSINESS UNIVERSITEIT

ISBN: 9789089801715