DNB Working Paper

No. 643 / July 2019

Security design and credit rating risk in the CLO market

Dennis Vink, Mike Nawas and Vivian van Breemen

DeNederlandscheBank

EUROSYSTEEM

Security design and credit rating risk in the CLO market

Dennis Vink, Mike Nawas and Vivian van Breemen *

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 643

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

July 2019

Security design and credit rating risk in the CLO market*

Dennis Vink[a], Mike Nawas[a] and Vivian van Breemen[b]

[a] *Nyenrode Business Universiteit, the Netherlands*
[b] *De Nederlandsche Bank, the Netherlands*

July, 2019

Abstract

In this paper, we empirically explore the effect of the complexity of a security's design on hypotheses relating to 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, which are more likely to have been catered by credit rating agencies to match each other. 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, investors do not value dual ratings more than single ratings in the determination of the offering yield at issuance. 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.

---

* 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. Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank. Corresponding authors: Dennis Vink (d.vink@nyenrode.nl), Mike Nawas (m.nawas@nyenrode.nl) and Vivian van Breemen (v.m.van.breemen@dnb.nl).

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 dominated and to date still 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, assigning biased ratings to structured products. Such biased ratings may have caused investors to misprice these securities (see, e.g., He, Qian, and Strahan (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, Barak, Brunnermeier, and Ge (2011), Carlin, Kogan, and Lowery (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 we broadly see two dominant theories that 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 U.S. and regulations in the European Union (E.U.) 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, E.U. regulations require issuers of structured finance securities to disclose at least two ratings.[1]

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

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

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, Parlour, and Rajan (2014)). A number of studies that focused on the run-up to the 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, Goldsmith- Pinkham, and Vickery (2011)).

In this paper, 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 E.U. 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 other words, if investors had assumed that issuers of complex deals would solicit two credit ratings, choose the most favorable credit rating and discarded the lowest one, they would have been incorrect. 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 to have applied 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 our first set of tests 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 of rating catering in the case of dual rated tranches and the extent to which they vary 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 (Güntay and Hackbarth (2010), Bongaerts, Cremers, and Goetzmann (2012), Moreira and Zhao (2018)). Consequently, we run our third set of tests and find 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 and hence price this credit rating risk at issuance.

Our results are 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 U.S. 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 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 a complexity characteristics in their security design. The sample construction and methodology are described in Section 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 4. In order to gain a further understanding of the role of complexity in the number of ratings, in Section 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 6 we answer the question whether investors are aware of the credit rating risk caused by rating catering and rating shopping behavior.

2. Literature on the credit rating process

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 U.S. (ESMA (2018), 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 and 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 and 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 U.S. 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, Palia, and Tang (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, Freixas, and Shapiro (2012)). For example, policy-makers in the U.S. introduced via the Dodd-Frank Act the requirement for the SEC to analyze rating processes and to reduce inconsistencies. Regulations in the E.U. are aimed at promoting a higher level of information disclosure and reducing over-reliance on credit ratings. In 2013, the E.U. implemented a new regulation that requires at least two credit ratings to be disclosed for newly issued structured products (European Union (2013)).

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, Qian, and Strahan (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 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 desire so. 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., Griffin, Nickerson, and Tang (2013), He, Qian, and Strahan (2016), Zhou, Xu, and Wang (2017), Flynn and Ghent (2018)). So, CRAs have an incentive to facilitate favorable ratings (see Sangiorgi, Sokobin, and Spatt (2009), Skreta and Veldkamp (2009), Flynn and Ghent (2018)). 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 model-implied differences in AAA tranche size were 10.5% on average between S&P and Moody's. However, the two CRAs agreed on the initial AAA tranche size in 96.3% of cases from 1997 to 2007. 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 among 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.

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 and 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 (Skreta and Veldkamp (2009), Bakalyar and Galil (2014)).

*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, Nawas, and Vink (2017)).

Ghent, Torous, and Valkanov (2019) analyze the U.S. 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, Deng, Nichols, and Sanders (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, Wang, and Wang (2018) use the number of tranches and tranche size to measure deal complexity.

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 empirically. 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 He et al. (2016) and Jian et al. (2018) who test for rating shopping 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. The direct effect of rating shopping is not visible as issuers are not obliged to disclose all ratings of preliminary assessments of CRAs (Sangiorgi and Spatt (2017)).

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: 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. 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. Data and Methods

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 U.S. or E.U. 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. 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.

3.2 ***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 coefficient on the yield for securities that received one or two credit ratings and the explanatory value as measured by R^2.

Based on our literature review in Section 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:

$$\begin{aligned} &Number\ of\ Ratings_{ijt} = \\ &\alpha_0 + \alpha_1 Tranche\ Count_{ijt} + \alpha_2 Tranche\ Size_{ijt} + \alpha_3 Capital\ Allocation_{ijt} + \\ &Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt} \end{aligned} \quad (1)$$

$$\begin{aligned} &Rating\ Discrepancy_{ijt} = \\ &\alpha_0 + \alpha_1 Tranche\ Count_{ijt} + \alpha_2 Tranche\ Size_{ijt} + \alpha_3 Capital\ Allocation_{ijt} + \\ &Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt} \end{aligned} \quad (2)$$

$$Spread_{ijt} =$$

$$\alpha_0 + \alpha_1 Tranche\ Count_{ijt} + \alpha_2 Tranche\ Size_{ijt} + \alpha_2 Capital\ Allocation_{ijt} + \quad (3)$$

$$Tranche, Issuer\ and\ Market\ controls + \varepsilon_{ijt}$$

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*).

3.3 *Variable Construction and Summary Statistics*

3.3.1 *Dependent Variables*

Table 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 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.[2] 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, and is measured 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 at issue. Looking at Panel B of Table 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).[3] Issuance spread is a measure of the risk premium demanded by investors. The reason this spread measure is used rather than secondary market spreads is that the latter vary throughout a tranche's life, being impacted by not only the

[2] 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.
[3] Almost all CLO tranches are issued at par. Where that was not the case, they were excluded from the sample.

rating but also by the collateral's performance (defaults and recoveries). This problem does not exist when using new issuance spreads. 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.

3.3.2 ***Design Characteristics of CLO Deal Complexity***

We report the descriptive statistics and variable distributions in Panels A and B of Table 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 allocation[4] 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[5] 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*, an 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 ***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*

[4] 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).
[5] We excluded one outlier with 29 tranches in one deal.

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 U.S. dollars. The mean *Transaction Value* of the sample is US$651 million. 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 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 1, the mean credit rating 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. Panel C of Table 1 also shows that 7.5% of the tranches received a single AAA rating from either Moody's or S&P, and 22.3% of the tranches received a dual AAA rating.

We also 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 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,* an dummy variable set to one if the security is issued in the E.U. market and zero if issued in the U.S. market. In the full sample, 38% of the securities (3,363 tranches) are issued in the E.U. and 62% in the U.S. (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.

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 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 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 and Becker (2018)) and their reaction by tightening standards thereafter, causing S&P since then to provide less favorable ratings than its competitor Moody's.[6] 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 caters its rating to match that of Moody's. Figure 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 2005 to 2007.

To control for other possible factors, we move to a multivariate regression framework. For our regression analysis in Equation (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 2 report the estimates of the logit tests of Equation (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, we repeat the analysis of Table 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.

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

4.1 ***Number of ratings disclosed at issuance***

In Table 2 we report the results of logit regressions with the number of credit ratings described above as the dependent variables. Panel A of Table 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 (Z-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: they remain positive and significant at a 1% significance level in all cases except for *Tranche Count*, where the indicators 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 2 we find that the magnitude of *Capital Allocation's* coefficient increases to an odds ratio of 2.38 (Z-stat=9.08), indicating that a one standard deviation increase in *Capital Allocation* increases the odds of a dual-rated tranche by 138%. 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 (Z-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 2, we report results for only AAA and non-AAA tranches, respectively. Looking at the pseudo R^2s of Table 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 results for the complexity characteristics. However, 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 a 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 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.

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, 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 results 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 2.

In Table 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 (Z-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 (Z-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, especially for CLOs with higher capital allocation levels, are more likely to shop for a single credit rating provided by Moody's rather than by S&P. 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 Moody's rating because Moody's would be the only CRA willing to engineer the deal with higher capital levels to obtain AAA status.

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.[7] 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 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 2005 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 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.

In Table 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 (6), 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 (Z-stat=2.04), column (3). The result

[7] 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.

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 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*. Overall, the results of Table 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. Apparently, issuers became less comfortable with reporting widely split ratings.

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. While 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), the yield at issuance is the dependent variable and the credit rating is the key independent variable, sorted by year and issuer fixed effects. Table 5, Panel A columns (1) and (2) 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 column (7) and (8). We are interested in the impact of the credit rating coefficient 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 Table 5, Panel A first suggest that investors do rely on CRAs in their risk assessment of the required yield, but they clearly differentiate between CRAs. Second, 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 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 do 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).

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.

7. Conclusion

The relevance to 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 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 E.U, 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 issuers take into account the complexity of a security's design in choosing the number of ratings at issuance. 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 substantially 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 E.U. 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 not be able to be placed in the market. Also, the regulations introduced regarding CLO ratings in the U.S. Dodd-Frank Act appear to disregard the investors' ability to differentiate between CRAs and between single-rated and dual-rated deals as they determine their investment yield requirements. Investors do rely on CRAs and take the number of CRAs involved in a deal into consideration.

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 U.S. Dodd-Frank Act, our recommendation would be to require CRAs, as they rate CLOs, to set out specifically their considerations in relation to the complexity characteristics that we found to be important to investors in their determination of the need for one or multiple ratings. Such disclosure will help both issuers and investors to make better-informed decisions about which CRA to engage, and the consequences thereof on yield requirements.

References

An, Xudong, Yongheng Deng, Joseph B. Nichols, and Anthony B. Sanders, 2015, What is subordination about? Credit risk and subordination levels in commercial mortgage-backed securities (CMBS), *Journal of Real Estate Finance & Economics* 51, 231–253.

Arora, Sanjeev, Boaz Barak, Markus Brunnermeier, and Rong Ge, 2011, Computational complexity and information asymmetry in financial products, *Communications of the ACM* 54, 101–107.

Ashcraft, Adam, Paul Goldsmirth-Pinkham, Peter Hull, and James Vickery, 2011, Credit ratings and security prices in the subprime MBS market, *American Economic Review* 101, 115–19.

Baghai, Ramin, and Becker Bo, 2018, Reputations and credit ratings: Evidence from commercial mortgage-backed securities, *CEPR Discussion Papers 12648.*

Bakalyar, Inna, and Koresh Galil, 2014, Rating shopping and rating inflation in Israel, *International Review of Financial Analysis* 33, 270–280.

Becker, Bo, and Todd Milbourn, 2011, How did increased competition affect credit ratings? *Journal of Financial Economics* 101, 493–514.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro, 2012, The credit ratings game, *Journal of Finance* 67, 85–111.

Bongaerts, Dion, Martijn Cremers, and William Goetzmann, 2012, Tiebreaker: Certification and multiple credit ratings, *Journal of Finance* 67, 113–152.

Carlin, Bruce I., Shimon Kogan, and Richard Lowery, 2013, Trading complex assets, *Journal of Finance* 68, 1937–1960.

De Haan, Jakob, and Fabian Amtenbrink, 2011, Credit rating agencies, *DNB Working Paper No. 278*.

Dimitrov, Valentin, Darius Palia, and Leo Tang, 2015, Impact of the Dodd-Frank act on credit ratings, *Journal of Financial Economics* 155, 505–520.

European Union, 2013, Regulation 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.

European Securities and Markets Authorities (ESMA), 2018, Report on CRA market share calculation, https://www.esma.europa.eu/sites/default/files/library/cra_market_share_calculation_2018.pdf.

Fabozzi, Frank J., Mike E. Nawas, and Dennis Vink, 2017, Exploring rating shopping for European triple a senior structured finance securities, *Finance Research Letters* 20, 35–39.

Fahad, Nafiz U., and Mehnaz R. Laura, 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, 907–920.

Flynn, Sean, and Andra Ghent, 2018, Competition and credit ratings after the fall, *Management Science* 64, 1477–1973.

Furfine, Craig, 2014, Complexity and loan performance: Evidence from the securitization of commercial mortgages, *Review of Corporate Finance Studies* 2, 154–187.

Ghent, Andra, Walter N. Torous, and Rossen I. Valkanov, 2019, Complexity in structured finance, *The Review of Economic Studies* 86, 694–722.

Golan, Limor, Christine A. Parlour, and Uday Rajan, 2014, *Competition, managerial slack, and corporate governance*, Working Paper, University of Michigan.

Griffin, John M., and Dragon Y. Tang, 2012, Did subjectivity play a role in CDO credit ratings? *Journal of Finance* 67, 1293–1328.

Griffin, John M., Jordan Nickerson, and Dragon Y. Tang, 2013, Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings, *Review of Financial Studies* 26, 2270–2310.

Güntay, Levent, and Dirk Hackbarth, 2010, Corporate bond credit spreads and forecast dispersion, *Journal of Banking and Finance* 34, 2328–2345.

He, Jie, Jun Qian, and Philip E. Strahan, 2011, Credit ratings and the evolution of the mortgage-backed securities market, *American Economic Review* 101, 131–135.

He, Jie, Jun Qian, and Philip E. Strahan, 2012, Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities, *Journal of Finance* 67, 2097–2137.

He, Jie, Jun Qian, and Philip E. Strahan, 2016, Does the market understand rating shopping? Predicting MBS losses with initial yields, *Review of Financial Studies* 29, 457–485.

Jiang, John X., Isabel Y. Wang, and K. Philip Wang, 2018, Revolving rating analysts and ratings of MBS and ABS: Evidence from LinkedIn, *Management Science* 64, 5461–5959.

Kiesel, Florian, 2016, Do investors still rely on credit rating agencies? Evidence from the financial crisis, *The Journal of Fixed Income* 25, 20–31.

Kraft, Pepa, 2015, Do rating agencies cater? Evidence from rating-based contract, *Journal of Accounting and Economics* 59, 264–283.

Moreira, Fernando, and Zhao Sheng, 2018, Do credit ratings affect spread and return? A study of structured finance products, *International Journal of Finance & Economics* 23, 205–217.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435–480.

Sangiorgi, Francesco, Jonathan Sokobin, and Chester Spatt, 2009, Credit-rating shopping, selection and the equilibrium structure of ratings, *Working Paper, Carnegie Mellon University*.

Sangiorgi, Francesco, and Chester Spatt, 2017, Opacity, credit rating shopping, and bias, *Management Science* 563, 4016–4036.

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

Skreta, Vasiliki, and Laura Veldkamp, 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *Journal of Monetary Economics* 56, 678–695.

White, Halbert, 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Journal of the Econometric Society* 48, 817–838.

Zhou, Xiaoyang, Guangli Xu, and Yongjin Wang, 2017, The issuer-pays business model and competitive rating market: Rating network structure, *Journal of Real Estate Finance and Economics* 55, 216–241.

TABLE 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 U.S. 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 U.S. 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	19.95	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

TABLE 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 U.S. 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)	
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	8,931	8,931	8,944	8,931	8,931	8,931	8,931	8,931
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	2,407	2,407	2,413	2,407	2,407	2,407	2,407	2,407
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	6,270	6,270	6,276	6,270	6,270	6,270	6,270	6,270
R^2	0.415	0.415	0.405	0.404	0.420	0.433	0.416	0.416

TABLE 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 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)
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)	(0.578)	(1.929)	(2.108)
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)
Observations	7,313	7,313	7,320	7,313	7,313	7,313	7,313	7,313
Credit rating effects	Y	Y	Y	Y	Y	Y	Y	Y
Year effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.478	0.478	0.475	0.474	0.480	0.478	0.479	0.479

TABLE 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 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)
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

TABLE 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 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)
Control Variables								
Euro Market		-14.12**		110.4		-17.69		-8.89
		(-2.13)		(0.66)		(-1.14)		(-1.34)
Top Ten Issuer		31.96		-178.9**		116.4		38.82
		(1.34)		(-2.47)		(1.36)		(1.50)
Log Transaction Value		-9.60**		-5.65		-0.27		-9.30
		(-2.06)		(-0.53)		(-0.02)		(-1.51)
Year Effects	N	Y	N	Y	N	Y	N	Y
Issuer Fixed Effects	N	Y	N	Y	N	Y	N	Y
Observations	7,715	7,706	1,038	1,034	1,489	1,487	5,188	5,185
Adjusted R^2	0.515	0.737	0.290	0.648	0.553	0.836	0.559	0.747

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

Figure 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.

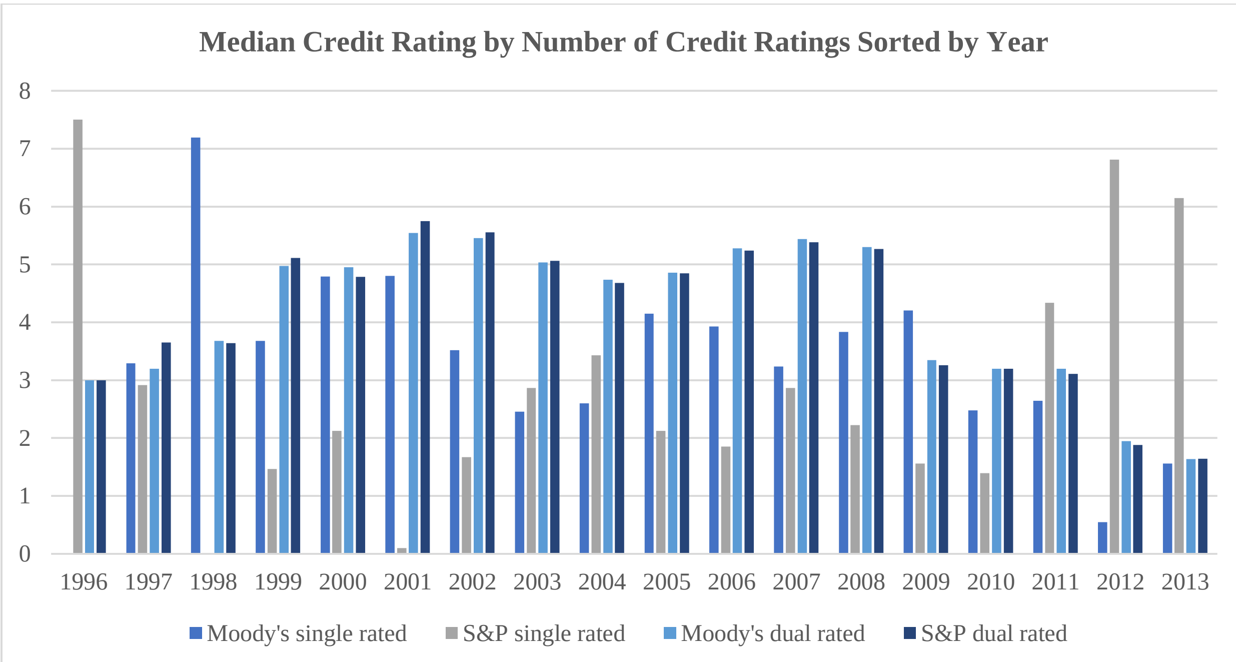

Figure 2: Rating Discrepancy between Moody's and S&P

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 is converted to a number equivalent. Figure 2(a) illustrates the rating discrepancy in notches tranches of Moody's and S&P sorted by year of issuance. The dots with larger dark surrounding represent a higher portion of tranches in the sample with rating discrepancy sorted by year of issuance and rating notch difference. Figure 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.

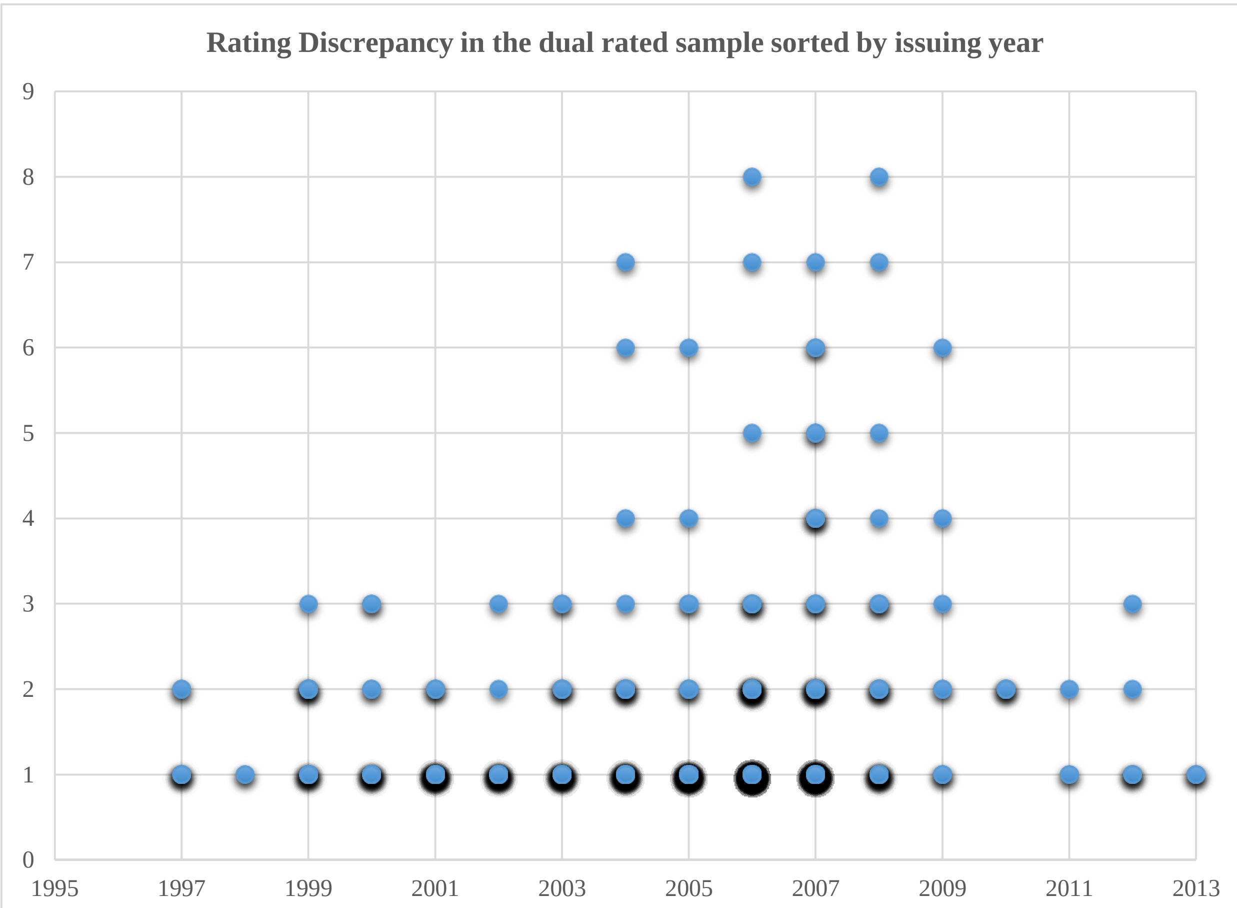

Figure 2(a)

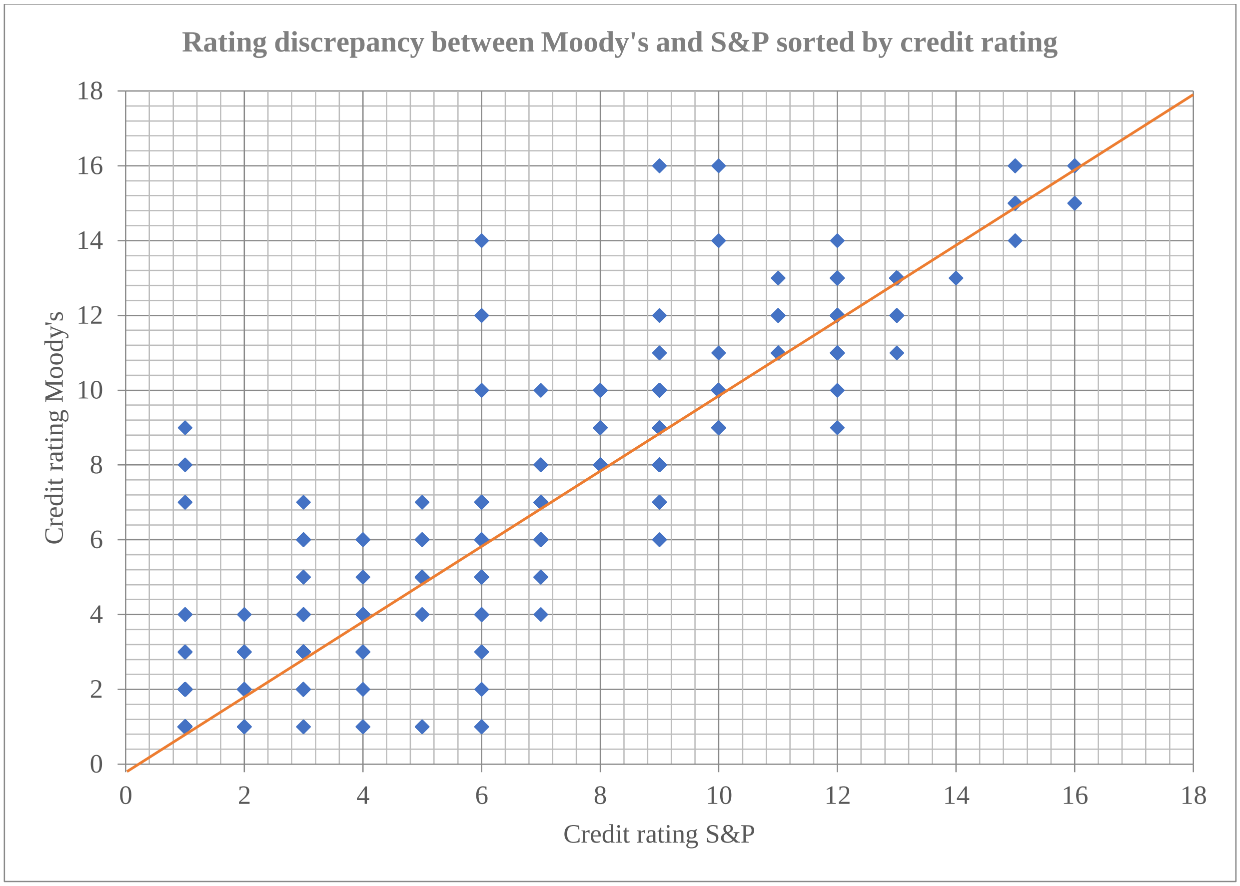
Rating discrepancy between Moody's and S&P sorted by credit rating
18
16
14
12
10
8
6
4
2
0
Credit rating Moody's
0
2
4
6
8
10
12
14
16
18
Credit rating S&P

Figure 2(b)

Previous DNB Working Papers in 2019

No. 622 **David-Jan Jansen,** Did Spillovers From Europe Indeed Contribute to the 2010 U.S. Flash Crash?
No. 623 **Wilko Bolt, Kostas Mavromatis and Sweder van Wijnbergen,** The Global Macroeconomics of a trade war: the EAGLE model on the US-China trade conflict
No. 624 **Ronald Heijmans and Chen Zhou,** Outlier detection in TARGET2 risk indicators
No. 625 **Robert Vermeulen, Edo Schets, Melanie Lohuis, Barbara Kölbl, David-Jan Jansen and Willem Heeringa,** The Heat is on: A framework measuring financial stress under disruptive energy transition scenarios
No. 626 **Anna Samarina and Anh D.M. Nguyen,** Does monetary policy affect income inequality in the euro area?
No. 627 **Stephanie Titzck and Jan Willem van den End,** The impact of size, composition and duration of the central bank balance sheet on inflation expectations and market prices
No. 628 **Andrea Colciago, Volker Lindenthal and Antonella Trigari,** Who Creates and Destroys Jobs over the Business Cycle?
No. 629 **Stan Olijslagers, Annelie Petersen, Nander de Vette and Sweder van Wijnbergen,** What option prices tell us about the ECB's unconventional monetary policies
No. 630 **Ilja Boelaars and Dirk Broeders,** Fair pensions
No. 631 **Joost Bats and Tom Hudepohl,** Impact of targeted credit easing by the ECB: bank-level evidence
No. 632 **Mehdi El Herradi and Aurélien Leroy,** Monetary policy and the top one percent: Evidence from a century of modern economic history
No. 633 **Arina Wischnewsky, David-Jan Jansen and Matthias Neuenkirch,** Financial Stability and the Fed: Evidence from Congressional Hearings
No. 634 **Bram Gootjes, Jakob de Haan and Richard Jong-A-Pin,** Do fiscal rules constrain political budget cycles?
No. 635 **Jasper de Jong and Emmanuel de Veirman,** Heterogeneity and Asymmetric Macroeconomic effects of changes in Loan-to-Value limits
No. 636 **Niels Gilbert,** Euro area sovereign risk spillovers before and after the ECB's OMT
No. 637 **Dorinth van Dijk,** Local Constant-Quality Housing Market Liquidity Indices
No. 638 **Francesco G. Caolia, Mauro Mastrogiacomo and Giacomo Pasini,** Being in Good Hands: Deposit Insurance and Peers Financial Sophistication
No. 639 **Maurice Bun and Jasper de Winter,** Measuring trends and persistence in capital and labor misallocation
No. 640 **Florian Heiss, Michael Hurd, Maarten van Rooij, Tobias Rossmann and Joachim Winter,** Dynamics and heterogeneity of subjective stock market expectations
No. 641 **Damiaan Chen and Sweder van Wijnbergen,** Redistributive Consequences of Abolishing Uniform Contribution Policies in Pension Funds
No. 642 **Richard Heuver and Ron Triepels,** Liquidity Stress Detection in the European Banking Sector

DeNederlandscheBank
EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl