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Structured debt ratings: Evidence on conflicts of interest ☆

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ABSTRACT

We test if issuers of asset- and mortgage-backed securities receive rating favors from agencies with which they maintain strong business relationships. Controlling for issuer fixed effects and a large set of credit risk determinants, we show that agencies publish better ratings for those issuers that provide them with more bilateral securitization business. Such rating favors are larger for very complex structured debt deals and for deals issued during the credit boom period. Our analysis is based on a new deal-level rating statistic that accounts for the full distribution of tranche ratings below the AAA cut-off point of a structured debt deal.

1. Introduction

In 2007 and 2008, credit rating agencies (CRAs) downgraded thousands of structured debt securities simultaneously by up to ten rating notches (Benmelech and Dlugosz, 2009; Ashcraft, GoldsmithPinkham, and Vickery, 2010). The large share of initially AAA-rated securities made market participants and regulators wonder if many ratings issued before 2007 had not been excessively favorable (e.g., Financial Stability Forum, 2008). In their lawsuit against the CRA Standard & Poor's (S&P), the US Department of Justice claims that S&P's concerns for their commercial relationships with issuers were an important source of the observed "inflation" of credit ratings. In this paper we analyze these alleged incentive problems and find that strong bilateral relationship ties between issuers and CRAs are indeed associated with rating favors.

Compared to the corporate bond market, the structured debt market is highly concentrated with few issuers repeatedly interacting with the same CRAs (Frenkel, 2014). The possibility that an issuer terminates its business relationship and takes rating and consulting business to a competitor constitutes a considerable threat to a CRA. CRAs could, therefore, cater rating favors to key clients to preserve or establish strong business ties. To examine this hypothesis, we compute the annual securitization business

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shared between a given issuer and each of the three major CRAs. As a proxy for bilateral relationship ties, the *Shared business* features considerable heterogeneity across CRA-issuer pairs. For example, over the period 1999 to 2011, Bank of America provides S&P with 76% more securitization business than Fitch, whereas Royal Bank of Scotland provides S&P and Fitch with roughly the same rating volume. Importantly, such heterogeneity enables us to control for unobserved issuer fixed effects such as issuer reputation or securitization expertise, which could impact credit ratings.

Cross-sectional variation in the credit risk of structured debt securities should correlate with credit ratings and could also be systematically correlated with different issuer types. Failure to control for credit risk can wrongly attribute rating favors to issuers with access to better collateral pools or higher levels of credit enhancement. We use a comprehensive new data set with information on collateral delinquency, type, and origin, liquidity reserves, bond insurance, and overcollateralization to control for differences in credit risk as much as possible.[2] As important credit risk proxies like collateral delinquency are only measured at the collateral pool or deal level, we do not analyze the tranches into which securitization deals are structured individually but conduct our analysis at the deal level.

For the deal-level analysis the tranche ratings of a structured debt deal need to be summarized into one deal-level rating statistic. Since credit ratings have an ordinal interpretation, we cannot simply define a size-weighted average but first need to translate the ratings into cardinal values. For each credit rating, we estimate the average yield spread of all tranches with this credit rating. This *Rating-implied spread* reflects the nonlinear relation between credit ratings and bond yields and is a cardinal measure. In a second step, we compute our *Deal rating* as the sum of the *Rating-implied spreads* weighted by the relative size of each deal tranche so that its units can be interpreted as a yield spread. Better tranche ratings translate into a lower *Deal rating* value.

Our sample comprises the credit ratings of more than 6,500 mortgage- and asset-backed securities (MBS and ABS) published by Moody's, S&P, and Fitch between 1999 and 2011. Based on the corresponding 1,404 deal-CRA pairs, we find that the *Shared business* represents an economically and statistically significant determinant of *Deal ratings* after controlling for credit risk and issuer fixed effects. An increase of the shared business volume between a given CRA and issuer by one standard deviation corresponds to an improvement (decrease) of the *Deal rating* by 41% relative to the sample average. CRAs publish better credit ratings for issuers with whom they maintain strong relationship ties. We interpret such preferential treatment for some issuers as a relative rating favor. The resulting loss of ratings accuracy is likely to foster mispricing, reduce market liquidity as observed during the financial crisis (Pagano and Volpin, 2010), and impede rating-contingent regulation (Efing, 2013).[3]

We also test what kind of deals issuers with strong relationship ties receive better ratings than other issuers. First, rating favors should be more pronounced for very complex products because regulators and investors might find it relatively harder to identify these rating favors and to discipline CRAs. Furthermore, deal complexity also makes information acquisition more expensive for CRAs themselves so that they might be more inclined to simply publish a favorable credit rating rather than spend resources on the production of accurate credit risk information. Consistent with this prediction, we find that issuers that share more business with a CRA receive particularly pronounced rating favors for complex deals structured into numerous tranches.

Second, incentives to cater rating favors should vary over the credit cycle. During credit booms when default probabilities and the reputational costs to ratings inflation are lower, CRAs are predicted to succumb more easily to the pressure of publishing inflated ratings for a key client. While the conflict of interests is important throughout the entire sample period, we find that relative rating favors are indeed more pronounced during the boom years 2004–2006.

Finally, we analyze differences across CRAs and asset classes and show that our results are not driven by a single agency or asset class. All three CRAs cater statistically significant rating favors to issuers with strong relationship ties and do so across asset classes. Yet, we find that S&P and Fitch tend to provide the largest relative rating favors for their key clients.

The papers closest to our contribution are He, Qian, and Strahan (2011, 2012). The authors take a "market valuation approach" by showing that investors require higher bond yields for MBS sold by issuers with a large market share, which is consistent with a risk premium for rating favors. Our approach differs in three ways. First, identification in this paper does not rely on market assessments of credit risk but directly compares ratings to a large set of credit risk controls. Second, we do not proxy conflicts of interest with the simple market share of an issuer but rather its *bilateral* business shared with a given CRA. This *Shared business* should be a better proxy for the varying relationships between CRAs and issuers and features more time variation than the issuers' overall market share. Third, our analysis is at the deal-level and not at the tranche-level so that we need to be less concerned about how the complex deal structures allocate credit risk to individual tranches.

Our paper is closely related to Hau, Langfield, and Marques-Ibanez (2013) who also compute the securitization business shared between a given issuer and a CRA. However, the authors do not relate this relationship proxy to structured debt ratings but show that a larger *Shared* (*securitization*) *business* correlates with more favorable corporate ratings of banks. Further papers on rating

[2] In unreported regressions we also control for excess spreads, constant prepayment rates, and credit default swaps of issuers. Our key results remain qualitatively unchanged.

[3] According to Hunt (2009), ratings played a role in at least 44 rules of the Securities and Exchange Commission (SEC) as of June 2008. Also, quasi-regulatory constraints often rely on the quality of credit ratings (Cantor, Gwilym, and Thomas, 2007).

failures include Griffin and Tang (2012), Griffin, Nickerson, and Tang (2013), and Cornaggia and Cornaggia (2013). Griffin and Tang (2012) find that CRAs make subjective adjustments to their computer models and that these adjustments lead to more severe rating downgrades later on. Griffin, Nickerson, and Tang (2013) show that the adjustments to the computer models are larger if competitive pressure on the CRAs is high. Cornaggia and Cornaggia (2013) compare the ratings of an issuer-pays agency (Moody's) with the ratings of a subscriber-pays agency (Rapid Ratings), and show that the subscriber-pays agency produces timelier and more accurate ratings.

Finally, our paper contributes a new deal-level rating statistic to a literature that has mainly relied on AAA subordination levels to analyze rating failures (e.g., Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; Stanton and Wallace, 2010). By definition, the AAA subordination level only makes a crude distinction between AAA and not-AAA ratings, whereas our *Deal rating* accounts for the full distribution of tranche ratings. If, for example, a large AAA tranche is only achieved by making the junior tranches particularly risky, our new *Deal rating* reflects this. It is very important to account for the entire rating scale as many relevant outcomes (e.g., financing costs, default rates, regulatory requirements, etc.) are highly sensitive to the lowest credit ratings of a deal.

The remainder of this paper is organized as follows. Section 2 spells out the testable hypotheses and relates them to the theoretical literature. The data and the construction of the variables *Shared business* and *Deal rating* are described in Section 3. Section 4 presents our empirical findings, Section 5 discusses their robustness, and Section 6 concludes.

2. Hypotheses

Incentives to grant rating favors arise because CRAs earn a substantial share of their income from the issuers whose securities they rate. While this was not always the case—until the 1970s, credit ratings were paid for by investors (White, 2010)—today the big three CRAs (Moody's, S&P, and Fitch) have all adopted the issuer-pays model. Issuers can threaten to withhold a rating mandate and to take their business to a competing CRA, which results in the loss of the publication fees for the rating: “Typically, the rating agency is paid only if the credit rating is issued, though sometimes it receives a breakup fee for the analytic work undertaken even if the credit rating is not issued” (SEC, 2008). The strong bargaining position of some issuers may make CRAs lenient in their credit risk assessment so that they cater rating favors to maintain and attract rating business.

The CRAs often argue that their concerns for maintaining their reputation keep conflicts of interest inherent in the issuer-pays model in check. However, reputational costs can be insufficient to discipline CRAs if there is a large number of “trusting” investors of limited attention or information processing ability (Bolton, Freixas, and Shapiro, 2012) or if investors reap large regulatory benefits of biased ratings (Efing, 2013; Opp, Opp, and Harris, 2013). In the highly concentrated structured debt market in particular, where few issuers repeatedly transact with the same CRAs, reputational concerns could be of secondary importance compared to the more immediate concerns about the relationship ties to a key issuer (Frenkel, 2014). In its call for civil money penalties against S&P, the US Justice Department documents how S&P's top managers involved so-called Client Value Managers in the rating process:

On July 1, 2004, *Rose and Gillis circulated a memorandum titled* “*Global Structured Finance Criteria Process*” […] *The memorandum recognized a role for S&P Client Value Managers* (*CVMs*), *who had* “*responsibility for managing the commercial relationship with clients*,” *in* “*criteria discussion*,” *and indicated that the CVMs should be* “*consulted for client information and feedback*” *and their input should be included in seeking* “*market perspective*.” (US Justice Department, 2013, p. 40)

We proxy the relationship tie between a given issuer and CRA by the size of the rating business in structured debt shared by both parties. Issuers with strong relationship ties are predicted to receive better credit ratings for their structured debt deals. This is not to say that issuers with weak relationship ties necessarily receive accurate credit ratings in an absolute sense. We simply attempt to identify relative or differential rating favors for issuers in which CRAs have a large commercial interest.

Opp, Opp, and Harris (2013) relate rating bias to asset complexity and predict that CRAs inflate ratings that are particularly hard to rate and are subject to regulatory distortions. The complexity of structured debt deals makes information acquisition more expensive, which lowers CRAs' incentives to produce accurate ratings and potentially prevents third parties (for example, regulators) from exposing and disciplining inflating CRAs. Therefore, we expect the preferential treatment of bilaterally important issuers to be more pronounced for complex structured debt deals.

Incentives to cater rating favors could also depend on economic fundamentals that vary over the credit cycle. The short-term benefits of new rating business net of reputational costs are higher during market booms when default probabilities are low, income from fees is high, and competition for the best analysts is tough (Bar-Isaac and Shapiro, 2013). During boom periods CRAs could therefore be more inclined to cater rating favors (Bolton, Freixas, and Shapiro, 2012). Hence, we predict that preferential treatment of issuers with strong relationship ties is more pronounced during the boom years 2004–2006, prior to the financial crisis.

3. Data

3.1. Data sources

Our analysis is based on a data set combining information from several sources. Face values, the number of tranches per deal, issuance dates, asset types, national origins of collateral, and the names of issuers and providers of debt insurance are retrieved from DCM Analytics (Dealogic). We extract this information for all asset-backed (ABS) and mortgage-backed securities (MBS) that were

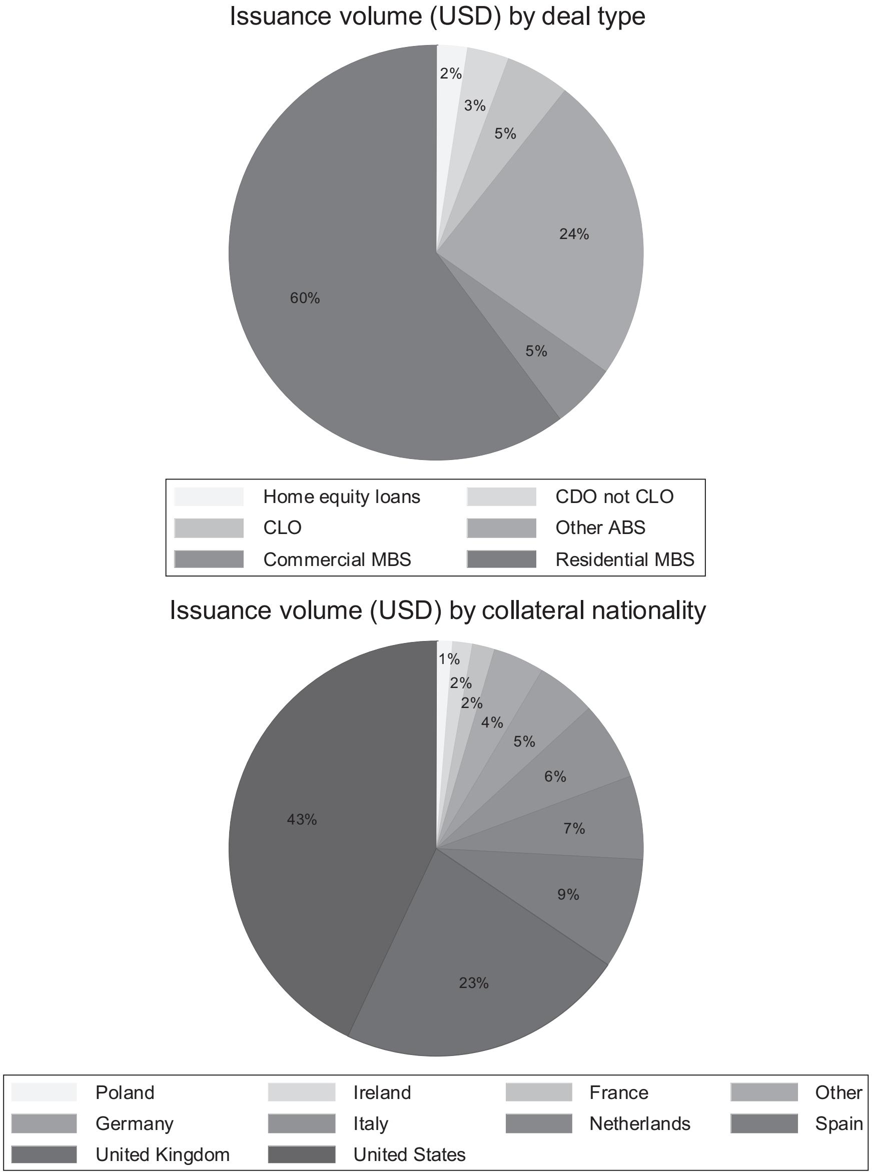

Fig. 1. The structured debt market is decomposed into different collateral types and national origins of the collateral. The issuance volume is computed as the total principal value in USD of all securities issued between 1999 and 2011. The sample comprises all securities that are backed by collateral from North America, Europe, Middle East, or Africa, have an ISIN identifier, and are reported by DCM Analytics. The total issuance volume is USD 6,968bn.

issued in Europe or North America between 1999 and 2011 and have an International Securities Identification Number (ISIN). The sample comprises 22,359 securitized tranches belonging to 7,255 deals. The total issuance volume (face value) in our sample is USD 6,968bn. These securities were sold by 949 different issuers.

Fig. 1 shows the composition of the total issuance volume in different asset types and the national origins of the collateral. Residential and commercial MBS account for 60% and 5% of the sample, respectively, and collateralized debt (CDO) and collateralized loan obligations (CLO) for 3% and 5%, respectively. Forty-three percent of the securities are backed by collateral from the USA, followed by 23% for collateral from the UK, and 9% for Spain. Fig. 2 shows the boom-bust pattern characterizing the structured debt market between 1999 and 2011. Between 1999 and 2003, market growth in our sample is relatively stable. During subsequent years issuance volumes increase and peak in 2007 when issuers are raising about six times the capital collected in 2003. The year 2007 marks the beginning of the financial crisis, seeing a reduction in liquidity, bank runs, massive downgrades of thousands of structured debt ratings, and a subsequent decline in issuance volumes.

DCM Analytics also provides the launch ratings published by Moody's, S&P, and Fitch at the time of security issuance.[4] A composite rating is determined for the 15,743

[4] We focus on launch ratings as the influence of market considerations on rating standards should be highest when a deal is rated for the

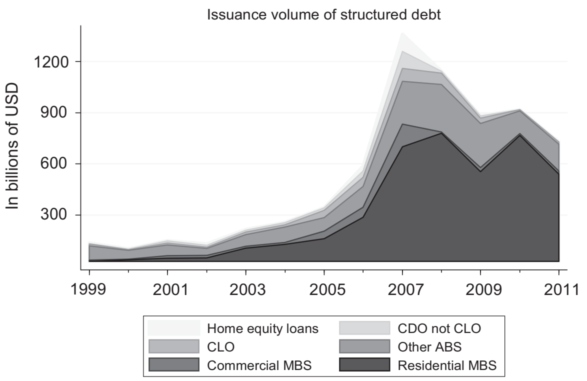

Fig. 2. The market growth of structured debt between 1999 and 2011. The issuance volume is computed as the total principal value in USD of all securities in a given year. The sample comprises all securities that have collateral from North America, Europe, Middle East, or Africa, are issued between 1999 and 2011, have an ISIN identifier, and are reported by DCM Analytics. The total issuance volume is USD 6,968bn.

securities with launch ratings from more than one CRA. If the security has two ratings, the more conservative rating is used. If the security has three ratings, the median rating is chosen.[5] Overall, 46% of all securities carry an AAA composite rating and 5% have a Junk composite rating, whereas 12% of the securities are not rated by any CRA.

Finally, we retrieve coupon information from DCM Analytics. Of the 22,359 securities, 70% are floating rate notes paying the London Interbank Offered Rate (Libor) or Euro Interbank Offered Rate (Euribor) plus a yield spread as a coupon. The average spread is 89 basis points (bps) and has a standard deviation of 104 bps. We augment the coupon information from DCM Analytics with Libor and Euribor rates from Thomson Reuters Datastream and issuance prices from Bloomberg. Information about the currencies in which the securities are issued and the weighted average life at security issuance also comes from Bloomberg. The tranche-level summary statistics are shown in Table 1.

The database Performance Data Services provided by Moody's contains information about the quality of collateral pools and the amount of credit enhancement of structured debt deals, which we use to control for the credit risk of 672 deals in the original sample retrieved from DCM Analytics. As a proxy of collateral pool quality, we use the cumulative delinquency rates defined as the fraction of collateral that is at least 90 days delinquent. The average delinquency rate measured nine months after deal closure is 1.29% and has a standard deviation of 2.37%.[6]

For any given collateral quality, different forms of credit enhancement can reduce the credit risk of a deal. *Overcollateralization* is measured as the difference between the total collateral principal value and the combined principal value of the deal tranches. The issuers can also set up a *Reserve fund* of cash to provide liquidity for interest and principal payments if the cash flows from the collateral pool become insufficient. The aggregate principal value of the deal tranches that benefit from debt insurance captures direct guarantees given by either an external party or by the issuer itself. We measure the variables *Overcollateralization*, *Reserve fund*, and *Deal fraction with guarantee* at the deal level and standardize them by the combined tranche principal of the deal. The average deal is slightly undercollateralized (mean *Overcollateralization* of -0.3%), the average *Reserve fund* equals 3% and approximately 6% of the average deal benefits of bond insurance.

After merging the different data sources we obtain 620 European and 52 North American deals (both ABS and MBS) that have been rated by at least one CRA and for which we have full data coverage over all variables. These deals were issued by 157 different issuers and carry 6,514 individual tranche ratings. The 1,404 corresponding deal-CRA pairs constitute the final sample for the regression analyses. Deal-level summary statistics for this regression sample are provided in Table 2. The variables *Overcollateralization*, *Reserve fund*, *Deal fraction with guarantee*, *Delinquency rate*, and the yield spreads are winsorized at the 2.5% level to reduce the impact of data errors but results are robust to not winsorizing the data (see Internet Appendix, Table A1). More details about the sample construction and the use of data filters are reported in the Internet Appendix.

3.2. Construction of new variables

Aggregating tranche ratings to deal-level. A deal-level analysis requires a translation of tranche ratings into an aggregate (deal-level) rating score. Since tranche ratings are ordinal, we cannot simply define a size-weighted average. Instead, we use the following two-step procedure. In a first step, we infer the average yield spread of a tranche rating from a linear pricing model. Let y denote the yield spread at issuance of tranche tr in deal d and $\mathbf{D} = (D_{AAA}, D_{AA+}, \ldots D_{Junk})$ a vector of dummy variables ($D_R \in \{0, 1\}$) marking the composite rating of the tranche. We use the linear pricing model

$$y = \alpha_D \mathbf{D} + \alpha_Z \mathbf{Z}_{tr} + \epsilon, \tag{1}$$

where the vector $\mathbf{Z}_{tr}$ controls for tranche, deal, and market characteristics. The *Rating-implied spread* (*RIS*) is defined as the fixed effect $RIS = \{\widehat{\alpha}_D\}_R$ capturing the average launch spread of all tranches with the same composite rating R. Importantly, the *RIS* can capture any nonlinear relationship between tranche ratings below AAA and the average yield spread at issuance.

In a second step, we aggregate the *RIS* values of the tranches to the deal-level. Let the function $RIS(a, d, tr)$: $tr \rightarrow RIS$ denote the *RIS* that CRA a provides to the issuer by assigning a rating R to tranche tr in deal d. Using the asset weights ω_{tr} for all n tranches in a structured deal, we

(*footnote continued*)
first time. Indeed, Griffin and Tang (2011) show that S&P's business division in charge of launch ratings applies lower rating standards than its ratings surveillance division.

[5] This procedure is consistent with the "most prevalent institutional rule used for classifying rated bonds" (Bongaerts, Cremers, and Goetzmann, 2012, p. 114) and is also used under the Standard Approach of Basel II (Basel Committee on Banking Supervision (BCBS), 2006, p. 24).

[6] If no observation for the delinquency rate exists nine months after deal closure, the closest observation between six and 12 months after deal closure is chosen and linearly adjusted. See Internet Appendix for details.

Table 1
Tranche-level summary statistics.
Reported are summary statistics on the tranche-level characteristics, the market term structure data at issuance, and the imputed *Rating-implied spread* (*RIS*). Composite ratings are determined for securities with ratings from more than one CRA: If a security has two ratings, the more conservative rating is documented. If the security has three ratings, the median rating is chosen. PDS is short for Moody's database Performance Data Service, DCM is short for DCM Analytics, Bloomb. stands for Bloomberg, Datastr. stands for Thomson Reuters Datastream, and calcul. abbreviates calculated.

Variable	Description	Source	Obs	Mean	Median	Std. dev.	Min	Max
Panel A: Tranche characteristics								
Yield spread	To Euribor or Libor in %	DCM	10,625	0.89	0.50	1.04	0.03	4.50
Tranche face value	Face value in USD	DCM	22,359	312*m*	71*m*	867*m*	404	64.7*bn*
Log tranche face value		calcul.	22,359	18.20	18.08	1.76	6.00	24.89
Issuance price	In % of face value	Bloomb.	13,427	99.81	100	3.45	1.09	214.85
Weighted avg. life	At issuance in years	Bloomb.	17,706	5.55	4.97	3.62	0.1	33.82
Panel B: Composite rating dummies								
AAA	1 for ratings shown	calcul.	22,359	0.46	–	–	–	–
AA+/AA/AA−	1 for ratings shown	calcul.	22,359	0.11	–	–	–	–
A+/A/A−	1 for ratings shown	calcul.	22,359	0.13	–	–	–	–
BBB+/BBB/BBB−	1 for ratings shown	calcul.	22,359	0.12	–	–	–	–
Junk	Rating below *BBB−*	calcul.	22,359	0.05	–	–	–	–
Unrated senior/mezzanine/junior	Unrated, not subordinated to any *rated* tranche	calcul.	22,359	0.09	–	–	–	–
Unrated mezzanine/junior	Unrated, only subordinated to rated mezzanine tranche	calcul.	22,359	0.02	–	–	–	–
Unrated junior	Unrated, subordinated to rated junior tranche	calcul.	22,359	0.01	–	–	–	–
Panel C: Term structure at issuance (in %)								
Term structure level	1mth US Libor	Datastr.	22,355	3.27	3.58	2.09	0.19	6.82
Term structure slope	12mth minus 1mth US Libor	Datastr.	22,355	0.34	0.28	0.44	−0.82	1.73
Panel D: Rating implied credit spread (in %)								
RIS(Moody's)	Implied by Moody's rating	calcul.	22,359	0.35	0.26	0.53	0.00	2.61
RIS(S&P)	Implied by S&P rating	calcul.	22,359	0.35	0.06	0.57	0.00	2.61
RIS(Fitch)	Implied by Fitch rating	calcul.	22,359	0.36	0.44	0.41	0.00	2.61

define the *Deal rating* as

$$Deal\ rating(d, a) := \sum_{tr=1}^{n} \omega_{tr} \cdot RIS(a, d, tr). \qquad (2)$$

As *Deal rating* averages over the *RIS* of all tranches *tr* of deal *d*, its units can again be interpreted as a yield spread measured in bps. A deal with good tranche ratings—and, hence, low *RIS*—has a low value of *Deal rating*.

We estimate the relation in Eq. (1) in a sample of 10,625 European and North American floating-rate notes that are issued at par and have the Libor or Euribor as base rate. Our analysis includes dummies for unrated tranches to account for the fact that the absence of a rating for a certain tranche also conveys information. For example, if the lowest-rated tranche has a BB+ rating, then we can infer that the unrated tranche is of worse quality than BB+ (see Internet Appendix for details).

In Table 3, column 1, credit ratings fixed effects are reported without further controls and explain 48% of variation in launch spreads. All coefficients are highly significant and show small standard errors. Adding fixed effects for the issuance half-year, asset type, collateral nationality, and currency, as well as their time-interactions, increases the regression R^2 from 0.484 to 0.703 in column 2. Column 3 includes additional controls for tranche-level characteristics such as *Log tranche face value* (and its squared value) as liquidity proxies and *Weighted avg. life* (and its squared value) as a maturity control.[7] In column 4 we follow the literature and control for the level and slope of the term structure at the time of issuance (Duffee, 1998).[8]

We use the complete specification in Table 3, column 4 to estimate the fixed effects on the credit ratings. Then we aggregate these *RIS* to the deal-level and compute the *Deal rating* defined in Eq. (2).[9] Table 2 provides summary statistics for the *Deal ratings* in the final regression sample. The largest number of *Deal ratings* in the regression sample is obtained for Moody's (620 observations), followed by S&P (433), and Fitch (351). The average *Deal rating* is slightly higher for Moody's (11 bps) than for S&P and Fitch (both 10 bps).

[7] According to Firla-Cuchra (2005), *Weighted avg. life* is a more meaningful maturity measure than the nominal maturity in the case of securitization due to structured cash-flows and embedded prepayment options.

[8] The variables *Term structure level* and *Term structure slope* are defined as the one-month USD Libor rate and as the difference between the 12-month and the one-month USD Libor rate, respectively.

[9] We include unrated tranches and unsecuritized "equity tranches" in the computation of the *Deal rating*. See Internet Appendix for details.

Table 2
Deal-level summary statistics.

Reported are summary statistics on the deal characteristics, the imputed *Deal rating*, AAA subordination levels, and *Shared business* for the final regression sample. *Delinquency* is measured nine months after deal closure. If no observation with nine months' seasoning exists, the delinquency observation closest to nine months seasoning (at least six and at most 12 months' seasoning accepted) is chosen and linearly adjusted (see Internet Appendix). For *Overcollateralization* and *Reserve fund* the youngest available observation after deal closure is chosen (at most six months' seasoning accepted). PDS is short for Moody's database Performance Data Service, DCM is short for DCM Analytics, and calcul. abbreviates calculated.

Variable	Description	Source	Obs	Mean	Median	Std. dev.	Min	Max
Panel A: Deal characteristics								
Deal face value	Face value in USD	DCM	672	2.08*bn*	1.18*bn*	4.01*bn*	77.10*m*	69.5*bn*
Log deal face value	Natural log of deal face value	calcul.	672	20.94	20.89	0.91	18.16	24.96
Delinquency	Winsorized fraction (in %) of delinquent collateral 9mth after deal closure	PDS	672	1.29	0.35	2.37	0.00	12.17
Log delinquency	Log(*Del.* + 0.0053)	calcul.	672	−1.01	−1.04	1.70	−5.23	2.50
Deal fraction with guarantee	Winsorized ratio of guaranteed principal over deal face value	DCM	672	0.06	0.00	0.21	0.00	1.00
Overcollateral.	Winsorized ratio of collateral principal minus principal of securities over principal of securities	PDS	672	−0.003	0	0.05	−0.13	0.21
Reserve fund	Winsorized reserves divided by principal of securities	PDS	672	0.03	0.02	0.03	0	0.13
Number of tranches	No. of deal tranches	DCM	672	4.84	4	2.90	1	26
Unsecuritized deal part	Ratio of deal face value minus principal of securities over deal face value	calcul.	672	0.01	0	0.07	0.00	0.98
Single CRA	1 if all tranche ratings from same CRA	calcul.	672	0.24	–	–	–	–
Panel B: Deal rating (in %)								
Deal rating (*S&P*)	Implied by S&P ratings	calcul.	433	0.10	0.04	0.21	0	1.98
Deal rating (*Moody's*)	Implied by Moody's ratings	calcul.	620	0.11	0.04	0.20	0	1.98
Deal rating (*Fitch*)	Implied by Fitch ratings	calcul.	351	0.10	0.04	0.21	0	1.98
Deal rating	*Deal rating* of all deal-CRA pairs	calcul.	1,404	0.10	0.04	0.21	0	1.98
Log deal rating	Log(*Deal rating* + 0.0030)	calcul.	1,404	−3.14	−3.17	1.29	−5.82	0.68
Panel C: AAA subordination levels								
AAA subord. (*S&P*)	Deal fraction not AAA by S&P	calcul.	433	0.22	0.08	0.32	0	1
AAA subord. (*Moody's*)	Deal fraction not Aaa by Moody's	calcul.	620	0.19	0.08	0.29	0	1
AAA subord. (*Fitch*)	Deal fraction not AAA by Fitch	calcul.	351	0.13	0.08	0.16	0	1
AAA subord.	Deal fraction not AAA by any CRA	calcul.	1,404	0.19	0.08	0.28	0	1
Log AAA subord.	Ln(*AAA subord.*+ 0.0070)	calcul.	1,404	−2.35	−2.44	1.17	−4.96	0.01
Panel D: Shared Business								
Shared business	Business (USD) between CRA a and issuer of deal d over 12 months	calcul.	1,404	10.20*bn*	3.60*bn*	18.2*bn*	12.6*m*	120*bn*
Log shared business	Natural log of *Shared business*	calcul.	1,404	22.04	22.00	1.44	16.35	25.51

Using Eq. (2) to compute a deal-level rating statistic has the advantage that we account for the distribution of tranche ratings below the AAA threshold. Although AAA subordination levels, defined as the fraction of the deal below the AAA cut-off point, are generally low (see Table 2), the highly non-linear relationship between credit ratings and yield spreads suggests the inclusion of *all* tranche ratings in the deal-level aggregation. The low correlation between our *Deal rating* and the AAA subordination level of 0.55 confirms that accounting for the ratings of mezzanine and junior tranches is important.

We argue that our consecutive analysis is robust to the exact specification of the *RIS* function as long as it approximately reflects the nonlinear relationship between tranche ratings and most relevant outcomes (market yields, regulatory capital requirements, default probabilities, etc.). To illustrate this, we replace our estimated *RIS* function with an alternative function called *Rating-implied capital charges* (*RICC*), which determines capital requirements for US life insurance companies (Becker and Opp, 2014) and converts tranche ratings into numbers from 0.4% to 30%. We replicate our consecutive analysis by substituting the *RIS* function with the alternative *RICC* function and obtain qualitatively very similar results (see Internet Appendix, Table A2).

Measuring relationship ties between issuer and CRA. Our analysis examines the relationship between *Deal rating* and the relationship-specific ties between issuers and CRAs. We proxy the strength of the business relationship between a given issuer and CRA at the time a deal is rated by the *Shared business*, namely, the combined securitization business that the issuer has with the CRA:

$$\textit{Shared business}(d,a) := \sum_{tr \in \Omega(d,a)} \textit{face value}\ (tr), \tag{3}$$

Table 3
Estimating rating-implied spreads.

We regress tranche-level yield spread on tranche rating and various control variables, which include *Log tranche face value* as well as its squared value; the *Weighted average life* of the tranche at issuance as well as its squared value; the one-month USD Libor rate at issuance as a proxy for the *Term structure level*; the difference between the 12-month and the one-month USD Libor rate at tranche issuance as a proxy for the *Term structure slope*. Time fixed, asset-type fixed, collateral nationality fixed, and currency fixed effects as well as their time-interactions are included in columns 2 to 4. Standard errors (in parentheses) are clustered for deals. The symbols *,**, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Dependent variable: *Yield spread*			
	(1)	(2)	(3)	(4)
Rating dummies:				
AA+	0.114***	0.090***	−0.005	−0.002
	(0.040)	(0.032)	(0.038)	(0.038)
AA	0.148***	0.182***	0.004	0.008
	(0.018)	(0.013)	(0.019)	(0.019)
AA−	0.196***	0.248***	0.059*	0.059*
	(0.036)	(0.027)	(0.031)	(0.031)
A+	0.434***	0.463***	0.245***	0.241***
	(0.055)	(0.037)	(0.039)	(0.038)
A	0.407***	0.472***	0.260***	0.264***
	(0.021)	(0.016)	(0.023)	(0.023)
A−	0.627***	0.587***	0.280***	0.282***
	(0.060)	(0.047)	(0.049)	(0.050)
BBB+	1.014***	1.091***	0.720***	0.718***
	(0.104)	(0.078)	(0.076)	(0.075)
BBB	0.961***	1.056***	0.776***	0.780***
	(0.034)	(0.028)	(0.033)	(0.033)
BBB−	1.060***	1.195***	0.883***	0.885***
	(0.057)	(0.044)	(0.048)	(0.048)
Junk	2.818***	2.933***	2.607***	2.609***
	(0.047)	(0.043)	(0.052)	(0.052)
Unrated senior/mezzanine/junior	0.666***	0.598***	0.434***	0.441***
	(0.047)	(0.052)	(0.056)	(0.055)
Unrated mezzanine/junior	1.457***	1.089***	0.995***	0.999***
	(0.189)	(0.153)	(0.179)	(0.178)
Unrated junior	2.443***	2.189***	2.013***	2.016***
	(0.316)	(0.318)	(0.379)	(0.378)
Controls:				
Log tranche face value			−0.617***	−0.617***
			(0.126)	(0.127)
Log tranche face value squared			0.014***	0.014***
			(0.003)	(0.003)
Weighted avg. life			0.025***	0.024***
			(0.006)	(0.006)
Weighted avg. life squared			−0.001***	−0.001***
			(0.000)	(0.000)
Term structure level				−0.159***
				(0.028)
Term structure slope				−0.241***
				(0.043)
Fixed effects & interactions:	No	Yes	Yes	Yes
R^2	0.484	0.703	0.730	0.733
N	10,625	10625	9314	9314

where $\Omega(d, a)$ is the set of all tranches rated by CRA a and sold by the issuer of deal d in the 12 months $[t-6, t+6]$ surrounding the issuance date t of deal d.[10] We concede that *Shared business* accounts only for the volume in structured products and ignores other business relationships between an issuer and a CRA—yet structured product ratings were the single most important income source for CRAs (Mathis, McAndrews, and Rochet, 2009).

Two arguments justify the choice of *Shared business* as a measure of potential conflicts of interest. First, as a bilateral measure, it allows us to control for issuer fixed effects—unlike an aggregate market share measure, which is likely to be persistent in time. Second, *Shared business* is a good proxy for the relationship-specific ties between the issuer and the CRA. Table 4 shows exploitable heterogeneity in issuer-CRA relationships in terms of issuer rank and rated issuance volume over the period 1999–2011 for the ten largest issuers by agency. For example, Royal Bank

[10] Our results are robust to the use of a larger symmetric window $[t-12, t+12]$ as well as to the forward-looking windows $[0, t+6]$ and $[0, t+12]$. These results are reported in Internet Appendix, Table A3.

Table 4
Top 10 issuers by credit rating agency.
Panel A shows the top 10 issuers according to the total securitization business shared between a given issuer and CRA over the years 1999 to 2011. Panel B shows total *Shared business* (aggregated over the years 1999 to 2011) in USD bn for each credit rating agency and issuer listed in Panel A.

Panel A: Top 10 issuers ranked by total Shared business (1999 to 2011)

Rank	Moody's	S&P	Fitch
1	Banco Santander	Banco Santander	Lloyds Banking
2	Lloyds Banking	Lloyds Banking	Banco Santander
3	Royal Bank of Scotland	Royal Bank of Scotland	Royal Bank of Scotland
4	Barclays	Bank of America	Northern Rock
5	Bank of America	Barclays	Barclays
6	Northern Rock	JPMorgan	JPMorga
7	Rabobank Nederland	Northern Rock	Bank of America
8	JPMorgan	Lehman Brothers	ABN AMRO Bank
9	Lehman Brothers	ABN AMRO Bank	Lehman Brothers
10	ABN AMRO Bank	Deutsche Bank	Nationwide Building Society

Panel B: Total Shared business (1999 to 2011)

Issuer	Moody's	S&P	Fitch
Banco Santander	285	314	248
Lloyds Banking	264	286	269
Royal Bank of Scotland	191	164	164
Barclays	164	125	97
Bank of America	136	157	89
Northern Rock	109	109	101
Rabobank Nederland	105	32	21
JPMorgan	102	110	89
Lehman Brothers	88	102	67
ABN AMRO Bank	84	92	69
Nationwide Building Society	52	52	52
Deutsche Bank	25	67	22

of Scotland has an equally large rating business with both S&P and Fitch of USD 164bn, whereas Bank of America provides S&P with 76% more rating business than Fitch, namely, USD 157bn and USD 89bn, respectively. For Moody's, Rabobank provides four times more rating volume than Deutsche Bank, whereas for S&P, Deutsche Bank provides more than twice as much rating volume as Rabobank.

4. Empirical analysis

We estimate the relation between *Deal rating* from Eq. (2) and *Shared business* from Eq. (3). *Deal rating*(d,a) represents the average yield spread implied by the credit ratings from CRA a for all tranches of deal d. A deal with a high *Deal rating*(d,a) value has received bad credit ratings for its tranches. *Shared business*(d,a) is the amount of securitization business that the issuer of deal d generates for CRA a and proxies the relationship ties between CRA and issuer. The extreme positive skewness of the variables *Deal rating* and *Shared business* (5.2 and 3.3, respectively) suggests a logarithmic transformation $Log(variable+k)$, where k is the constant that reduces the skewness of the transformed variable to zero.[11] The analysis is carried out in a linear regression model in which standard errors are clustered both by deal and by issuer:

$$Log\ deal\ rating(d,a) = \beta_{SB}\ Log\ Shared\ business(d,a) + \beta_C \mathbf{C}(d) + \epsilon. \quad (4)$$

The coefficient of interest β_{SB} is expected to be negative if CRAs publish better ratings for the deals of issuers that provide them with more securitization business.

Since cross-sectional variation in *Deal rating* should correlate with the credit risk of deals, it is important to include the controls $\mathbf{C}(d)$ for collateral quality, proxied by collateral delinquency,[12] and credit enhancement in the form of overcollateralization, liquidity reserves, and direct bond guarantees. As delinquency definitions and their reporting can differ somewhat across various collateral classes, we use additional asset-type fixed effects as well as fixed effects for the national origin of the collateral to control for such differences as much as possible. We also include the number of tranches in a deal, as the optimal design of deal structures could respond to collateral quality and credit enhancement, so that it becomes an additional measure of credit risk. Issuer fixed effects control for differences in the reputation, management skill, and creditworthiness of the issuer and the value of any implicit promises of liquidity or credit support that investors and CRAs could expect from the issuer of a deal.

[11] The results are robust to this logarithmic transformation (see Internet Appendix, Table A1).

[12] We use the log transformation $Log(delinquency+k)$ to reduce the skewness to zero (see remark above).

Table 5
Relationship ties and rating favors.

The (log) *Deal rating* is regressed on the (log) *Shared business*, which proxies the strength of the relationship ties between a given CRA and the issuer of a deal. The controls are: *Log deal face value* = natural logarithm of deal face value; *Log delinquency* = logarithm of collateral delinquency as well as its squared value; *Deal fraction with guarantee* = face value of guaranteed tranches divided by deal face value; *Overcollateralization* = difference between collateral and securities' principal divided by principal of securities; *Reserve fund* = liquidity reserves standardized by principal of securities; *No. of tranches* = number of deal tranches; constant (unreported). Column 5 uses the full sample of deals (except deals issued by Fannie Mae, Freddie Mac, or Ginnie Mae). If data on the delinquency rate, overcollateralization, or reserve funds are missing, we set these values to zero (only in column 5) and include dummies that indicate missing values as additional controls. Standard errors (in parentheses) are clustered in two dimensions both by deal and by issuer. The symbols *,**, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Dependent variable: *Log deal rating*				
	(1)	(2)	(3)	(4)	(5)
Log shared business	−0.195**	−0.285***		−0.273***	−0.234***
	(0.078)	(0.083)		(0.081)	(0.049)
Log deal face value			−0.158*	−0.070	−0.169**
			(0.088)	(0.085)	(0.072)
Controls:					
Log delinquency	0.216***	0.234***	0.203***	0.228***	0.035
	(0.081)	(0.082)	(0.077)	(0.081)	(0.051)
Log delinquency squared	0.036**	0.044**	0.040**	0.042**	0.001
	(0.018)	(0.017)	(0.017)	(0.017)	(0.013)
Deal fraction with guarantee	−0.531**	−0.310*	−0.301	−0.342*	−0.489***
	(0.244)	(0.177)	(0.201)	(0.177)	(0.162)
Overcollateralization	−1.248	−0.384	−0.333	−0.392	0.323
	(1.105)	(1.515)	(1.509)	(1.506)	(1.112)
Reserve fund	3.236	1.097	2.279	1.210	1.707
	(3.870)	(3.815)	(3.816)	(3.777)	(3.433)
No. of tranches	0.151***	0.142***	0.134***	0.146***	0.205***
	(0.038)	(0.033)	(0.036)	(0.035)	(0.020)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Collateral nationality fixed effects	Yes	Yes	Yes	Yes	Yes
Asset-type fixed effects	Yes	Yes	Yes	Yes	Yes
Issuer fixed effects	No	Yes	Yes	Yes	Yes
Dummies for missing values					Yes
R^2	0.316	0.551	0.536	0.551	0.535
N	1,404	1,404	1,404	1,404	8,544

The full vector of controls $\mathbf{C}(d)$ in Eq. (4) is given as

$$\mathbf{C}(d) = \{Log\ delinquency,\ Log\ delinquency\ squared,\ Deal\ fraction\ with\ guarantee,\ Overcollateralization,\ Reserve\ fund,\ Number\ of\ tranches,\ Asset\ type,\ Collateral\ nationality,\ Time,\ and\ Issuer\ fixed\ effects\}. \tag{5}$$

Table 5, column 1 presents a first regression that controls for various deal characteristics, but does not account for issuer heterogeneity. The coefficient for *Log shared business* is negative and statistically significant at the 5% level; issuers with more rating business tend to receive better tranche ratings than their competitors for deals with the same characteristics. In column 2, we also control for issuer heterogeneity by including issuer fixed effects. The coefficient on *Log shared business* now captures relative rating favors that the same issuer receives from different CRAs with which the issuer has heterogeneous bilateral rating volume. The coefficient becomes more negative and statistically highly significant. The inclusion of issuer fixed effects raises the R^2 notably from 32% to 55%, which suggests that issuer characteristics like creditworthiness, reputation, or management skills are important determinants of structured debt ratings. We can also highlight the economic significance of the variable *Shared business*: The coefficient value of −0.285 implies that an increase of *Log shared business* by one standard deviation (1.44) translates into a reduction in *Deal rating* by 41%. This corresponds to an improvement (reduction) of the *Deal rating* by 4 bps for a representative deal with an average *Deal rating* of 10 bps.[13]

The regression coefficients of the controls $\mathbf{C}(d)$ have the expected signs except for *Reserve fund*. In all specifications, deals with a high delinquency rate have lower ratings, implying significantly higher *Deal ratings*. The regression coefficients on *Deal fraction with guarantee* and *Overcollateralization* are both negative, whereas *Reserve fund* is positively correlated with *Log deal rating*. Deals with higher credit enhancement in the form of bond insurance and overcollateralization tend to have better ratings, which imply lower spreads; yet only the coefficient on *Deal fraction with guarantee* is significant (except in column 3). In all specifications the coefficient on *No. of*

[13] One standard deviation in *Log shared business* is 1.44 (see Table 2). Since our dependent variable is the log of *Deal rating*, an increase of *Log shared business* by 1.44 reduces *Deal rating* by $1.44 \times 28.5\% = 41.04\%$. According to Table 2, the average *Deal rating* over the deal-CRA pairs in the final regression sample is 10 bps and a decrease of 41% corresponds to 4 bps.

tranches is statistically significant and positive. Deals structured into a relatively large number of tranches receive on average lower credit ratings, either because the design of deal structures responds to collateral quality or because CRAs rate very complex deals more cautiously.

We also explore whether issuers obtain better ratings for larger deals. Larger deals could either increase the bargaining power of the issuers or provide better credit risk diversification. In Table 5, column 3 the coefficient on *Log deal face value* is indeed negative and statistically significant at the 10% level. Yet including both the conflict of interest proxy *Log shared business* and the *Log deal face value* in column 4 shows clearly that the former is the relevant explanatory variable, whereas the latter becomes statistically insignificant.

Finally, we seek to validate our results for the much larger sample used by He, Qian, and Strahan (2012). In column 5, we include deals without data on delinquency rates, overcollateralization, or reserve funds to increase the sample size but continue to exclude deals issued by Fannie Mae, Freddie Mac, or Ginnie Mae. The specification includes the dummy variables *Missing Delinquency*, *Missing Overcollateralization*, and *Missing Reserve Fund*, which identify observations with missing values in the control variables. The resulting sample comprises 8,544 observations from 4,337 different deals, which have received 33,539 individual tranche ratings. While roughly 80% of these observations miss data on at least one of the controls, the highly significant regression coefficient on *Log shared business* suggests that the evidence for our conflict of interest hypothesis extends to the full sample.

Deal complexity and rating favors. The incentives of CRAs to grant rating favors could vary with deal complexity. Higher deal complexity renders the evaluation of credit risk more difficult and (possibly) more expensive. Higher costs for agencies to produce accurate ratings, as well as for third parties like regulators to detect rating favors, might increase the inclination of agencies to bias ratings in favor of issuers with which they have close relationship ties. To test this prediction we interact *No. of tranches*, as a proxy for deal complexity, with the conflict of interest proxy *Log shared business*. Table 6, column 1, reports a negative and highly significant coefficient on *No. of tranches* $\times$ *Log shared business*, which supports the hypothesis that relative rating favors are stronger for more complex deals.

Business cycle effects. The incentives for CRAs to provide more favorable ratings to key clients might be strongest during credit booms when default probabilities and reputational costs to ratings inflation are relatively low. Issuers generating substantial rating business for a CRA are predicted to receive large relative rating favors during the structured debt boom from 2004 to 2006. By contrast, such rating favors should be less pronounced during the financial crisis when risk-aversion, perceived uncertainty, and default probabilities are high. To test this hypothesis, we define the credit boom dummy *Issued 2004–2006* and the crisis dummy *Issued 2007–2008* and interact them with the conflict of interest proxy *Log shared business*. We choose 2007 as the beginning of the financial crisis because the reduction in funding liquidity and events like the bank run on Northern Rock caused significant stress for the financial system in that year (Brunnermeier, 2009). Table 6, column 2 reports the regression coefficients of the two interaction terms. As time-fixed effects are already included in the specification, the boom and the crisis dummies need not be added separately. The coefficient on the interaction *Issued 2004–2006* $\times$ *Log shared business* is negative and significant at the 5% level. The coefficient for *Log shared business* remains statistically significant, which suggests that conflicts of interest also exist outside the credit boom period. The coefficient on the interaction term for the financial crisis is statistically insignificant, which indicates that relative rating favors during the crisis decrease to the pre-boom level before 2004 and is consistent with the massive rating downgrades that took place in 2007 and 2008 (Benmelech and Dlugosz, 2009).[14]

Differences across CRAs. We check whether our results are driven by CRA fixed effects, which could represent important determinants of deal ratings, as Moody's, S&P, and Fitch do not necessarily use the same rating methodologies. For example, expected loss is central in Moody's risk assessment whereas S&P and Fitch focus on default probabilities. Moreover, the interpretation of rating categories need not be the same across CRAs. An AAA rating by S&P could be intended to imply a different default rate than an AAA rating by Fitch. Table 6, column 3, controls for such CRA fixed effects and finds that they are statistically insignificant.

Next we analyze if the sensitivities to *Log shared business* differ across CRAs. Column 4 includes CRA dummies and their interactions with *Log shared business*. The coefficient on *Log shared business* itself remains negative and highly significant for all three CRAs—implying that the previous results are not driven by a single CRA. Instead, all three CRAs produce better ratings for the issuers that are most important in terms of their bilateral rating volume.

Nevertheless, the regression coefficients on the CRA dummies and their interactions with *Log shared business* suggest that agency conflicts differ across CRAs. The sign and value of the coefficients of the CRA dummies alone should signify whether S&P or Fitch attribute better or worse ratings than Moody's when rating favors are controlled for. By contrast, the sign and value of the coefficients on the interaction terms show which CRAs are more susceptible to relationship-based rating favors. The coefficients on the S&P and on the Fitch dummy are large and significant, suggesting that both agencies attribute stricter ratings than Moody's when rating favors are controlled for. At the same time, the interaction terms *S&P* $\times$ *Log shared business* and *Fitch* $\times$ *Log shared business* are negative and highly significant, indicating that the relationship-based favors are more pronounced for S&P and Fitch.

[14] We also test for a non-linear effect of the conflict of interest proxy on *Deal Rating* and partition *Log Shared Business* into the 25% lowest and 25% highest values. Regression results reported in Table A4 of the Web Appendix suggest that high *Shared Business* issuers receive worse and low *Shared Business* issuers receive better ratings after 2006. Agencies seem to adjust their ratings in both issuer groups during the subprime crisis. However, the statistical significance of the non-linear effect is low.

Table 6
Asset complexity, credit cycles, and agency fixed effects.

The (log) *Deal rating* is regressed on the (log) *Shared business*, which proxies the strength of the relationship ties between a given CRA and the issuer of a deal. Column 1 includes an interaction term between *Log shared business* and the *No. of tranches* in the deal. Column 2 includes two interaction terms between credit boom and crisis dummies and *Log shared business*. Column 3 includes CRA fixed effects and column 4 additionally includes interactions between CRA dummies and *Log shared business*. The controls are: *Log delinquency* = logarithm of collateral delinquency as well as its squared value; *Deal fraction with guarantee* = face value of guaranteed tranches divided by deal face value; *Overcollateralization* = difference between collateral and securities' principal divided by principal of securities; *Reserve fund* = liquidity reserves standardized by principal of securities; *No. of tranches* = number of deal tranches; constant (unreported). Standard errors (in parentheses) are clustered in two dimensions both by deal and by issuer. The symbols *,**, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Dependent Variable: *Log deal rating*			
	(1)	(2)	(3)	(4)
Log shared business	0.070	−0.173**	−0.289***	−0.245***
	(0.103)	(0.084)	(0.084)	(0.082)
No. of tranches × *Log shared business*	−0.071***			
	(0.018)			
Issued 2004–2006 × *Log shared business*		−0.295**		
		(0.120)		
Issued 2007–2008 × *Log shared business*		−0.074		
		(0.108)		
Dummy: *S&P*			−0.091	1.543**
			(0.055)	(0.671)
Dummy: *Fitch*			−0.036	1.807***
			(0.041)	(0.682)
S&P × *Log shared business*				−0.074***
				(0.030)
Fitch × *Log shared business*				−0.083***
				(0.031)
Controls:				
Log delinquency	0.203**	0.237***	0.235***	0.234***
	(0.080)	(0.079)	(0.083)	(0.082)
Log delinquency squared	0.044***	0.043***	0.044***	0.044***
	(0.016)	(0.017)	(0.017)	(0.017)
Deal fraction with guarantee	−0.398**	−0.299	−0.312*	−0.317*
	(0.165)	(0.182)	(0.178)	(0.179)
Overcollateralization	−0.149	−0.294	−0.372	−0.343
	(1.419)	(1.496)	(1.511)	(1.504)
Reserve fund	2.878	0.457	1.082	1.109
	(3.348)	(3.932)	(3.815)	(3.817)
No. of tranches	1.808***	0.144***	0.142***	0.143***
	(0.425)	(0.033)	(0.033)	(0.033)
Time fixed effects	Yes	Yes	Yes	Yes
Collateral nationality fixed effects	Yes	Yes	Yes	Yes
Asset-type fixed effects	Yes	Yes	Yes	Yes
Issuer fixed effects	Yes	Yes	Yes	Yes
R^2	0.577	0.559	0.551	0.553
N	1,404	1,404	1,404	1,404

Differences across asset types. Cornaggia, Cornaggia, and Hund (2014) show that the outcome of the rating process differs across different asset classes of structured products. We check if rating favors are different for ABS and MBS ratings. Table 7 reports the coefficients of separate regressions for MBS and ABS in columns 1 and 2.[15] The negative correlation between *Log deal rating* and *Log shared business* is stronger in the case of MBS, suggesting more pronounced rating favors than in the ABS market. However, the regression coefficient on an interaction term between *Log shared business* and a dummy variable for ABS deals is not significant when estimated in the full sample comprising ABS as well as MBS deals (column 3).

5. Robustness

The previous literature has identified low levels of AAA subordination as indicative of ratings inflation (e.g., Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; He, Qian, and Strahan, 2011). A small deal share of tranches rated below AAA reduces the cushion that can absorb losses before the senior tranches of a deal are impaired. Issuers have incentives to lobby for low AAA subordination levels because subordinated junior and mezzanine tranches can only be sold at relatively high yield spreads. In a first step, we conduct a simple nonparametric analysis by checking if a CRA gives an AAA rating to a larger share

[15] Residential and commercial MBS form the sample in column 1. All remaining asset classes are subsumed under ABS in column 2.

Table 7
Conflicts of interest across asset types.

The (log) *Deal rating* is regressed on the (log) *Shared business*, which proxies the strength of the relationship ties between a given CRA and the issuer of a deal. Column 1 considers the subsample of MBS and column 2 the subsample of ABS. Column 3 considers the full sample and includes an interaction of *Log shared business* with a dummy equal to one for ABS deals. Further dummies for commercial and residential MBS as well as for CLOs are included. The controls are: *Log delinquency*=logarithm of collateral delinquency as well as its squared value; *Deal fraction with guarantee*=face value of guaranteed tranches divided by deal face value; *Overcollateralization*=difference between collateral and securities' principal divided by principal of securities; *Reserve fund*=liquidity reserves standardized by principal of securities; *No. of tranches*=number of deal tranches; constant (unreported). Standard errors (in parentheses) are clustered in two dimensions both by deal and by issuer. The symbols *,**, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Dependent Variable: *Log deal rating*		
	MBS (1)	ABS (2)	All (3)
Log shared business	−0.341***	−0.185*	−0.341***
	(0.094)	(0.109)	(0.096)
ABS × Log shared business			0.128
			(0.134)
Controls:			
Log delinquency	0.215**	0.342*	0.215*
	(0.108)	(0.207)	(0.110)
Log delinquency squared	0.017	0.124***	0.017
	(0.016)	(0.043)	(0.016)
Deal fraction with guarantee	−0.205	−1.269	−0.205
	(0.206)	(0.851)	(0.211)
Overcollateralization	−1.886	2.580**	−1.886
	(1.899)	(1.199)	(1.938)
Reserve fund	−3.186	14.057**	−3.186
	(6.039)	(5.637)	(6.165)
No. of tranches	0.130***	0.274***	0.130***
	(0.032)	(0.074)	(0.033)
Dummy: *residential MBS*			2.836
			(2.938)
Dummy: *commercial MBS*	1.073**		3.909
	(0.333)		(3.001)
Dummy: *CLO*		−0.115	−0.403
		(0.499)	(0.493)
Time fixed effects	Yes	Yes	Yes
Collateral nationality fixed effects	Yes	Yes	Yes
Issuer fixed effects	Yes	Yes	Yes
Interactions: *ABS dummy × Controls*	No	No	Yes
R^2	0.540	0.778	0.622
N	1,059	345	1,404

of a deal when the issuer is among its most important customers in the securitization market.[16]

Table 8 shows the average AAA subordination level for all deals of the top 10% (top 5%) clients by CRA. The top clients are those issuers with the highest securitization business shared with the agency and aggregated over the period 1999–2011. The average deal share of subordinated tranches across all deals rated by Moody's is 33%. By contrast, the average subordination level that Moody's allows its 10% most important clients is only 26% and for the top 5% of clients it drops further to 25%. The result extends qualitatively to subordination levels granted by S&P and Fitch. A Wilcoxon rank-sum test compares the deals of the 10% (5%) top issuer clients against the deals of the remaining 90% (95%) less important customers of a CRA. The null hypothesis stating that the distributions of AAA subordination levels are identical in both samples is clearly rejected for all three CRAs. Similarly, we find that *Deal ratings* also improve significantly (have lower values) when deals are issued by the top 10% (top 5%) of clients of a given CRA. On average, deals issued by the 10% or 5% most important issuers that have the strongest relationship ties with a CRA benefit from lower AAA subordination levels and better *Deal ratings*.

We also analyze whether lower AAA subordination levels for deals of issuers with high *Shared business* are justified by higher collateral quality or more credit enhancement. We find that this is not the case. Collateral delinquency rates are significantly higher in the pools that back the deals of the top 10% or 5% of issuer clients. Furthermore, the deals of those issuers that generate the most rating business actually have less bond insurance. A statistically significant feature shared by the clients of all three CRAs concerns the size of deals and the number of tranches per deal, which are significantly larger for issuers that share a lot of rating business with a CRA.

[16] We conduct this analysis in the full sample whereas the sample used in Table 2 and in following regressions only uses deals with full data coverage on all control variables. However, deals issued by Freddie Mac, Fannie Mae, and Ginnie Mae are still excluded.

Table 8
Non-parametric test for rating favors.

Reported are average deal characteristics, the number of observations, and test results by CRA for (i) all deals rated, (ii) only the deals issued by the top 10% clients, and (iii) only the deals issued by the top 5% clients of the CRA in question. The top clients of a CRA are the largest issuers as identified by the securitization volume that they asked the CRA to rate between 1999 and 2011. Deals issued by Freddie Mac, Fannie Mae, and Ginnie Mae are excluded. The values of the variables *AAA subordination*, *Deal rating*, *Delinquency rate*, *Deal fraction with guarantee*, *Reserve fund*, and *Overcollateralization* are given in %. Under the null hypothesis of the Wilcoxon rank-sum test the deals of the top 10% (5%) clients are distributed like the deals of the 90% (95%) smallest clients. Columns 3, 6, and 9 provide the standardized test statistics, which are approximately normally distributed in large samples. The symbols *,**, and *** represent *p*-values of below 10%, 5%, and 1%, respectively.

	Moody's			S&P			Fitch		
	Obs. (1)	Value (2)	$\|z\|$−Stat (3)	Obs. (4)	Value (5)	$\|z\|$−Stat (6)	Obs. (7)	Value (8)	$\|z\|$−Stat (9)
AAA subordination									
All deals	3199	33.12		3655	34.99		1843	24.17	
Deals of top 10% clients	1842	26.06	11.85***	2168	28.17	12.52***	992	19.89	6.54***
Deals of top 5% clients	1460	24.54	11.64***	1800	26.87	13.03***	676	16.77	8.23***
Deal rating									
All deals	3199	18.57		3655	21.23		1843	16.26	
Deals of top 10% clients	1842	13.68	12.26***	2168	15.49	12.63***	992	14.04	5.52***
Deals of top 5% clients	1460	13.69	10.85***	1800	14.49	13.52***	676	11.57	7.07***
Delinquency rate									
All deals	622	1.24		435	1.60		351	1.58	
Deals of top 10% clients	429	1.44	3.44***	318	1.90	3.27***	226	1.92	2.72***
Deals of top 5% clients	324	1.55	1.93*	247	2.19	3.74***	138	2.03	1.82*
Deal fraction with guarantee									
All deals	3199	5.97		3655	5.27		1843	4.90	
Deals of top 10% clients	1842	4.35	3.67***	2168	3.65	4.78***	992	3.37	3.52***
Deals of top 5% clients	1460	4.10	3.59***	1800	3.13	6.17***	676	2.75	3.65***
Reserve fund									
All deals	622	2.65		435	2.07		351	1.94	
Deals of top 10% clients	429	2.61	0.42	318	2.08	0.38	204	1.99	0.74
Deals of top 5% clients	324	2.68	0.37	247	2.12	0.26	124	2.02	0.47
Overcollateralization									
All deals	622	−0.26		435	−0.07		351	0.02	
Deals of top 10% clients	429	−0.21	2.02**	318	0.08	0.30	204	0.26	0.05
Deals of top 5% clients	324	−0.06	1.02	247	0.37	1.01	124	0.79	1.61
No. of tranches									
All deals	3199	4.70		3655	4.46		1843	4.78	
Deals of top 10% clients	1842	4.76	3.54***	2168	4.55	2.62***	992	5.16	1.95*
Deals of top 5% clients	1460	4.80	2.81***	1800	4.43	5.81***	676	5.34	0.52
Deal face value									
All deals	3199	1.30*bn*		3655	1.11*bn*		1843	1.56*bn*	
Deals of top 10% clients	1842	1.71*bn*	16.39***	2168	1.44*bn*	16.38***	992	2.14*bn*	12.24***
Deals of top 5% clients	1460	1.79*bn*	12.80***	1800	1.45*bn*	11.68***	676	2.52*bn*	12.01***

Finally, we reproduce our baseline regression from Table 5, column 2 but use the (log) AAA subordination level as dependent variable. The regression coefficient on *Log shared business* in is -0.196 and statistically significant at the 1% level.[17] An increase of *Log shared business* by one standard deviation decreases the deal fraction that is subordinated to the AAA tranches by roughly 28% $(=1.44\times(-19.6)\%)$. Consistent with our previous results, issuers that generate a lot of rating income receive AAA ratings for larger deal parts.

[17] See Internet Appendix, Table A5, column 1 for the other regression coefficients.

6. Conclusion

Accurate credit ratings reduce informational asymmetries, whereas relative rating favors corrupt their information content and can distort the creation and allocation of credit risk. The reduced accuracy of ratings can also impede rating-contingent regulation with negative implications for financial stability. Motivated by the important role of credit ratings for the functioning of structured debt markets, we analyze relationship ties between issuers and CRAs as one important driver of rating favors.

We find evidence for systematic relative rating favors whenever CRAs have a strong bilateral client relationship with the issuer. Conditional on credit risk, an increase of the business volume shared between a CRA and issuer by one standard deviation improves the *Deal rating* by 41% relative to the sample average (a low *Deal rating* value corresponds to good tranche ratings). Such preferential treatment for some issuers constitutes an economically significant distortion of rating accuracy. To the extent that the pricing of structured products does not fully correct these rating favors, we expect additional distortions of the competitiveness of structured debt issuers.

Appendix A. Supplementary data

Supplementary data associated with this paper can be found in the online version at http://dx.doi.org/10.1016/j.jfineco.2014.11.009.

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