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ABSTRACT

Structured Debt Ratings: Evidence on Conflicts of Interest*

This paper tests for conflicts of interest in the rating process of European asset- and mortgage-backed securities based on a new aggregation method for a deal's different tranche ratings. Controlling for a large set of determinants of credit risk, we find that credit rating agencies provide better credit ratings for the structured products of those issuers that provide them with more overall bilateral rating business. This effect is particularly pronounced in the run-up to the subprime crisis and for structured products with the worst collateral. Rating favors to the largest clients generate economically significant competitive distortion, foster issuer concentration and contribute to the "too big to fail" status of large issuer banks.

JEL Classification: G01, G10 and G24
Keywords: conflicts of interest, credit ratings, ratings inflation and structured debt

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1 Introduction

After three years of rapid growth the structured debt market collapsed in the second half of 2007 when perceived creditworthiness suddenly deteriorated dramatically and credit rating agencies (CRAs) downgraded thousands of securities simultaneously (Benmelech & Dlugosz (2009b)). Since then CRAs have been facing increasing scrutiny by academics and regulators who wondered why about half of the structured securities had been given AAA ratings, thus putting the failure of the rating process at the very core of the subsequent global financial crisis.[1] A growing body of theoretical work relates positive rating bias to a conflict of interest of CRAs, which are paid by those whose securities they rate (for example Mathis *et al.* (2009) or Bolton *et al.* (2012)). This conflict of interest is presumably strongest in structured products (Harris *et al.* (2013)), which became an increasingly important revenue source for CRAs. Yet, deal complexity in thousands of individual securitization contracts and their market distribution through separate tranches presents a formidable obstacle to empirical research.

Our research contribution is twofold. First, we develop a new methodology for measuring rating bias in structured products based on aggregation of the tranche ratings to a deal level average rating statistic called *Deal Rating-Implied Spread* ($DRIS$). Second, we use this new measure to provide a more detailed picture of the competitive distortions characterizing the market for structured product ratings. Our focus is on the market power of large issuers, which we proxy by the *Agency Specific Securitization Business* ($ASSB$) between an issuer and a CRA. Such a measure of overlapping business interest is shown to be an economically large and statistically significant determinant of the rating favors an issuer bank obtained during the pre-crisis securitization boom. The securitization market therefore generated important competitive distortions in favor of large players in the securitization market, thus contributing to bank concentration and furthering the "too big to fail" status of large banks.

The complex contractual structures of most Asset Backed Securities (ABS) and Mortgage Backed Securities (MBS) pose great methodological challenges for their empirical analysis. Security issues are typically divided into several tranches of different seniority. Predefined loss triggers determine whether these tranches are amortized sequentially in the order of seniority

[1] AAA-rated MBS performed so badly that their ABX (reflecting the costs of insuring the index securities against default) dropped by around 70% between January 2007 and December 2008 (Brunnermeier (2009)).

or pro rata. The deal structure also determines under which circumstances interest payments are decoupled from principal payments and which tranches benefit from bond insurance or can tap liquidity reserves. Given such complex designs, CRAs simulate the cash-flow cascades of deals to determine the credit risk of individual tranches. An analysis of security ratings would have to do the same to accurately assess credit risk at the tranche level. To circumvent this challenge, we conduct our analysis of rating distortions at the deal level by summarizing the different tranche ratings of a deal into a single deal-level statistic. As credit ratings represent ordinal measures, we first map each tranche rating into a *Rating-Implied Spread* (RIS), which reflects the market value of any given tranche rating. Standard portfolio theory then allows us to aggregate the RIS into a *Deal Rating-Implied Spread* ($DRIS$) weighting the RIS by the relative size of each deal tranche. The $DRIS$ represents the market value of the overall deal rating and should be invariant to the specific intra-deal allocation of credit risk across different tranches. The existing literature uses the mere size of the AAA tranches to summarize the different tranche ratings of a deal (Ashcraft *et al.* (2010), He *et al.* (2011)), whereas our methodology provides a much more accurate market-based measurement of rating-implied deal quality.

Although the deal-level analysis allows us to ignore how deal structures allocate credit risk to different deal tranches, controlling for the overall credit risk of an ABS or MBS deal is important. We rely on a large set of factors determining collateral quality and credit enhancement at the deal level. The fraction of delinquent collateral measured nine months after the closure date of a deal proxies the quality of the collateral at the time when the deal received the launch ratings. Information on a deal's total liquidity reserves, overcollateralization and debt guarantees allow us to control for the amount of resources that enhance creditworthiness at the deal level.

Both the deal level rating statistic $DRIS$ and the controls for collateral quality and credit enhancement allow us to test a set of hypotheses about conflicts of interests in European structured debt ratings. For each pair (d, a) of a securitization deal d and a CRA a, we compute the Agency-Specific Securitization Business $ASSB(d, a)$ shared between the issuer and the CRA. The $ASSB$ represents the business volume in structured products of which an issuer can deprive the CRA. It is therefore a suitable measure of the strength of the negotiating position of the issuer vis-a-vis the CRA. Our conflict of interest hypothesis states that an issuer with a large $ASSB$ should be able to obtain rating favors from the particular CRA to which the issuer provides substantial business. The $ASSB$ proxy for "conflict of interest" features sufficient variation across rating agencies and time so that we can simultaneously control for issuer fixed effects, which separately account for the size, reputation and creditworthiness of an issuer. Our findings can be summarized as follows:

1. Based on a European sample of 1,501 deal-CRA pairs (d, a) with more than 6,600 individual tranche ratings produced by the three largest CRAs between 1999 and 2011, we find that the $ASSB$ measure represents an economically and statistically significant determinant of ratings favors. An increase of the business volume between the CRA and an issuer by two standard deviations corresponds to a decrease of the $DRIS$ by 75% or nine basis points (bp). CRAs therefore provided substantial rating favors to their largest clients.

2. Rating favors are twice as large for the 10% of deals with the highest overall credit risk compared to the rest of the credit risk distribution. Large issuers with a privileged relationship to a CRA lobbied more successfully for inflated ratings on the "credit risk lemons." As a consequence, they had incentives to market particularly overrated structured products of low overall credit quality. We also find weak evidence that rating favors were more pronounced for ABS deals with complex deal structures than for MBS deals.

3. Rating favors vary substantially over the credit cycle. Most of the rating favors coincide with the 2004–06 credit boom in the run-up to the financial crisis. Before and after this period of rapid credit and market expansion in structured products, the $ASSB$ proxy for conflict of interest is statistically insignificant.

4. We find evidence of "ratings shopping" during the credit boom. Between 2004 and 2006, deals with ratings from only one agency have *better* ratings than deals with ratings from several CRAs, suggesting that issuers suppress bad credit ratings. More pronounced rating favors during the same time period indicate that ratings shopping could have caused CRAs to compete on rating favors.

Our findings about the systematic link between rating favors and the CRAs' commercial interest with their largest issuer clients has wider implications for financial stability and reform. Rating favors based on business interests certainly distort the market for structured products and provide an undeserved competitive advantage to large issuers. The exorbitant asset growth of the largest banks may partly reflect such distortions in financing and issuing costs obtained through a distorted rating process. Hau, Langfield and Marques-Ibanez (2013) document independently that banks also obtain better corporate ratings from a CRA for which their $ASSB$ measure is large. From this perspective, the pre-dominance of large banks in the banking sector in general and for structured products in particular may be advanced by their economic power in the rating process rather than any competitive advantage. Size-contingent bank taxation may actually be pro-competitive.

A quality shortfall in the rating process has two other harmful economic consequences. First, if investors cannot internalize the conflict of interest to which CRAs are subject, distorted investment decisions are inevitable. The surge in mortgage default during the financial crisis suggests that a flawed rating system functioned as a channel through which large credit volumes were misallocated. Second, inflated ratings may allow banks to circumvent prudential capital requirements. In this case, the asset acquirer may be complicit and fully informed about the rating error. Efing (2012) shows theoretically how inflated asset ratings can contribute to a breakdown of bank capital regulation, with severe welfare costs.

This paper is closest to He *et al.* (2012), who find that investors required higher yields for MBS sold by large issuers. This finding is consistent with rating favors that are partially anticipated by investors. Alternatively, the deals of large issuers could simply exhibit risk factors unaccounted for by CRAs but priced by investors.[2] Therefore, we test directly for a systematic link between aggregate deal ratings and business relationships between CRAs and issuers rather than relying on market *expectations* about the *perceived* integrity of the rating process, like He *et al.* (2012).

In a related paper He *et al.* (2011) find that CRAs rate larger deal parts AAA if the deals

[2]For example, systematic risk could be one risk factor that is better accounted for by investors than by CRAs. Credit ratings reflect *physical* probabilities of default whereas asset prices depend on state prices and the distribution of payoffs across economic states (Coval *et al.* (2009)). If the deals of larger issuers exhibit higher systematic risk than the deals of small issuers, they will sell at different prices, even if they carry the same credit rating. To the extent that ratings are supposed to measure only physical default probabilities and not systematic risk, lower prices paid for the deals of large issuers do not allow us to infer the existence of rating favors.

are structured by large issuers. We improve their analysis (1) by controlling for collateral quality and credit enhancement and (2) by the use of *DRIS* as a new deal rating statistic that substantially increases the precision of inference on market distortions. While our analysis of rating favors is robust to the use of AAA subordination as dependent variable, *DRIS* accounts much more accurately for the large spectrum of different credit ratings than a crude distinction solely between AAA and *not*-AAA.

Ashcraft *et al.* (2010) predict mortgage defaults with a simple logit model based on observable credit risk factors. They use their model forecasts to adjust the fraction of deals rated AAA for ex-ante expectations of credit risk and show that rating standards progressively declined in the run-up to the financial crisis.[3] Griffin & Tang (2012) document that credit ratings experience more severe downgrades if rating analysts make subjective adjustments to the credit ratings suggested by their computer simulations. Griffin *et al.* (2013) find that the catering of rating favors is positively associated with competitive pressure in the rating industry. Cornaggia *et al.* (2012) analyze the ratings of analysts who leave their CRAs to work at the firms they rate. The authors document that these analysts become more favorable to their future employers. Benmelech & Dlugosz (2009b) find that ratings are more likely to be downgraded if ratings shopping is more aggressive. Several papers examine the empirical relationship between credit ratings and prices. Evidence in Ashcraft *et al.* (2011) suggests that ratings are causally related to MBS yield spreads. Firla-Cuchra (2005) find that ratings alone explain between 70% and 80% of variation in launch spreads on European structured bonds. Adelino (2009) shows that subprime MBS yield spreads are predictive for rating downgrades. Kisgen & Strahan (2010) investigates the influence of corporate bond ratings on financing costs and capital structure decisions.

The remainder of this paper is organized as follows. Section 2 spells out the testable hypotheses and relates them to the theoretical literature on ratings inflation. The data and methodology are described in Sections 3 and 4, respectively. Section 5 discusses the regressions and Section 6 their robustness. Section 7 concludes.

[3] The collateral quality of MBS deteriorated in the run-up to the crisis, whereas credit ratings remained optimistic. See also Demyanyk & Van Hemert (2011).

2 Hypotheses on Ratings Inflation

In this section we develop four hypotheses about the determinants of rating favors and conflicts of interest in the structured debt market. We focus on the question whether the business interests of CRAs in their issuer clients conflict with their mandate to produce unbiased credit risk information. As debt sells at a lower discount if it carries a higher rating (Firla-Cuchra (2005)), issuers have incentives to lobby for better ratings. A CRA might accommodate an issuer and *deliberately* inflate its ratings provided that its commercial interest in the issuer (and therefore the issuer's bargaining power) is sufficiently strong.

Incentives to grant rating favors arise because CRAs rely on the issuers they rate for their principal source of income. Since the 1970s issuers rather than investors normally pay the rating fees.[4] Importantly, issuers can choose freely between the ratings of competing CRAs and shop for the best rating (Skreta & Veldkamp (2009)). In exchange for a small break-up fee they can keep an already solicited credit rating confidential as they own the publication rights for solicited ratings (Mählmann (2008) and Faure-Grimaud *et al.* (2009)).[5] Thus, issuers may be able to capture CRAs that subsequently cater rating favors in order to maintain and attract rating business (Bolton *et al.* (2012)). If ratings are embedded in bank regulation, CRAs have additional incentives to inflate ratings because issuers of high-yield debt can share profits from regulatory arbitrage with CRAs (Efing (2012)).

We compute the Agency-Specific Securitization Business $ASSB$ that an issuer shares with a CRA. The $ASSB$ proxies the rating income of which an issuer can deprive the CRA. Hypothesis 1 predicts pronounced agency conflicts and rating favors for structured deals whose issuers have a high $ASSB$ with the CRA.

H1: Conflicts of Interest and Ratings Inflation

> Issuers that generate more rating business (i) receive better ratings and (ii) benefit from lower rating-implied spreads.

A distortive rating process may corrupt the informational value of ratings with two harmful consequences. First, sophisticated investors may distrust ratings and underinvest even in

[4] The investor-pays model was abandoned in the 1970s to reduce free-riding among investors (White (2010) and Pagano & Volpin (2010)).

[5] Ongoing regulatory reforms aim at reducing the possibility of ratings shopping.

correctly-rated assets because they fear purchasing a "lemon" (Akerlof (1970)). Second, naive or trusting investors might fail to anticipate conflicts of interest and overinvest in disguised credit risk (Bolton *et al.* (2012)). Furthermore, Hypothesis 1 predicts a structural relationship between the size of an issuer and conflicts of interest in the rating process. If large issuers that generate most rating fees get especially high rating favors, they will be able to refinance at lower rating-implied yields than small institutions. This competitive distortion contributes to issuer concentration and a "too big to fail" status. Finally, Hypothesis 1 is relevant for financial stability and reform because ratings inflation impedes rating-contingent regulation. Efing (2012) demonstrates how ratings inflation allows a risk-loving banking sector to arbitrage capital requirements that depend on the ratings of bank assets.[6]

Next, we refine Hypothesis 1 by asking which assets are particularly prone to deliberate ratings inflation. We first concentrate on the incentives of deal issuers to lobby for rating favors. The issuer benefit from a one-notch rating improvement depends on its position on the rating scale. For example, we estimate that an upgrade from *A+* to *AA-* is associated with an average yield reduction of 18*bp*, whereas an upgrade from *BBB+* to *A-* lowers the yield by on average 44*bp*. Given the much higher financing costs for securities with low credit ratings, very risky deals should stimulate more aggressive issuer lobbying so that rating favors will be more pronounced for the "credit risk lemons" in the market.

Second, the incentives of CRAs to inflate ratings are likely to depend on other factors besides the $ASSB$ generated by an issuer. Harris *et al.* (2013) relate rating bias to asset complexity and predict that CRAs will inflate ratings to facilitate regulatory arbitrage for deals that are particularly hard to rate. Deal complexity 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. As the average ABS deal in our sample features a more opaque deal structure and higher rating-implied credit risk than the average MBS deal, rating favors should be more pronounced for complex ABS (Hypothesis 2).

H2: Rating Favors by Deal Quality and Asset Type

Rating favors are concentrated in those deals for which they are most profitable to

[6] See also Calomiris (2009).

issuers and credit rating agencies.

(a) Structured deals of low quality benefit from larger rating favors as those are more profitable to issuers than rating favors on deals with already high credit ratings.

(b) More complex deals like ABS benefit from larger rating favors because high rating precision is more expensive and external quality verification more difficult.

Next, we relate the agencies' incentives to produce informative ratings to the state of the credit cycle. A number of theoretical models make predictions about *when* ratings accuracy is particularly low. Bar-Isaac & Shapiro (2011, 2012) link the performance of CRAs to the labor market for analysts. During credit booms, when default probabilities are low but demand for analysts is high, CRAs have little incentive to train analysts themselves or to compete with investment banks for the best analysts available. By contrast, during recessions, when default probabilities are high and competition for analysts by the banking industry is low, CRAs train and hire better analysts and rating accuracy increases.

Bolton *et al.* (2012) predict that CRAs' incentives to bias ratings are greater during credit booms when there are more trusting investors and the reputational costs to agencies of ratings inflation are low. Mathis *et al.* (2009) model confidence cycles. Initially CRAs are strict when a new innovative market is characterized by low issuance volumes. When CRAs have built a reputation for giving strict and accurate ratings and the market is expanding, the agencies start milking their reputation and inflate ratings. This continues until investors discover ratings inflation and the reputations of CRAs collapse along with issuance volumes.[7] We summarize this predicted relationship between conflicts of interest and credit cycles in Hypothesis 3.

H3: Conflicts of Interest over the Credit Cycle

Incentives for deliberate ratings inflation depend on the state of the credit cycle. Rating favors for issuers that generate high rating business are more pronounced during credit booms than in normal times.

If rating favors do indeed behave pro-cyclically, CRAs will contribute to the formation of asset price bubbles and increase the variability of the economic system. Instead of counter-

[7] Manso (2011) models the cliff effects at the time of a crash accounting for feedbacks of rating downgrades on the credit quality of issuers.

acting a distorted credit expansion to bad borrower types during booms, CRAs would facilitate their access to cheap financing.

Finally, we look for evidence of ratings shopping, that is the behavior of an issuer that publishes only good ratings and withholds unfavorable ratings instead of picking a rating randomly or publishing all available ratings (Sangiorgi *et al.* (2009)). As noted above, issuers can solicit indicative risk analyses from different CRAs and then publish only the most favorable credit ratings.[8] With rating methodologies becoming more transparent (Benmelech & Dlugosz (2009a)), issuers can even omit the stage at which they ask for indicative ratings and directly approach the CRA whose methodology will produce the best rating (Sangiorgi *et al.* (2009)).[9] Such ratings shopping might initiate a race to the bottom among CRAs, as each agency grants rating favors to deter an issuer from suppressing its rating.

The probability that an issuer suppresses a second or third credit rating should depend on the value that investors associate with the additional information conveyed by multiple ratings. In markets where precision is of greater value issuers should suppress ratings less often (Doherty *et al.* (2012)) because each rating lowers the lemons discount on high-quality deals that suffer from adverse selection. In contrast, at times when perceived asymmetric information is low and investors value multiple ratings less, issuers should suppress ratings more aggressively. We conjecture that ratings shopping is more pronounced during credit boom periods when investors are less risk-averse and high-quality deals suffer less from adverse selection.

Skreta & Veldkamp (2009) show that published ratings suffer from a winner's curse when issuers suppress bad ratings and only high ratings survive ratings shopping.[10] During credit booms, when bad ratings are more likely to be suppressed, single-rated deals should on average have better ratings than deals carrying ratings from several CRAs. During normal times when issuers shop less aggressively and publish multiple ratings about their high-quality deals to reduce lemon discounts, only the low-quality deals carry ratings from a single CRA and these single-rated lemons should, on average, have worse ratings (Hypothesis 4).

[8] Securities and Exchange Commission (SEC) (2008): "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." (p.9)

[9] Issuers that frequently buy their ratings from the same CRA will have a good idea which ratings and potential favors they can expect from *their* (potentially more lenient) agency and refrain from business with other CRAs.

[10] See also Sangiorgi *et al.* (2009).

H4: Ratings Shopping over the Credit Cycle

(a) During credit booms risk aversion and perceived asymmetric information are low. Issuers suppress bad credit ratings so that deals rated by only one CRA have, on average, better ratings.

(b) In normal times issuers publish multiple ratings to mitigate adverse selection. Only very risky deals with, on average, worse ratings are rated by just one CRA.

3 Data

Our analysis is based on a dataset 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 issued in Europe or North America between 1999 and 2011 and have an ISIN identifier. The sample comprises 22,359 securitized tranches belonging to 7,118 deals. The total issuance volume (face value) is USD 6,968bn. These securities were sold by 970 different issuers.[11]

Figure 1 shows the composition of the total issuance volume into different asset types and national origins of the collateral. Residential and commercial MBS account for 60% and 5% of overall issuance, respectively. ABS add up to 24%, followed by collateralized loan obligations (CLO) with 5%, and collateralized debt obligations (CDO) with 3%. Home equity loans constitute the smallest share of only 2%. In terms of collateral origin, 43% of the securities are backed by collateral from the USA, followed by 23% for collateral from the UK and 9% for Spain.

Figure 1

Figure 2 shows the boom-bust pattern characterizing the structured debt market between 1999 and 2011. Between 1999 and 2003 issuance volumes were relatively stable. However, market growth accelerated during subsequent years. The market size peaked in 2007 when issuers were raising about six times the capital collected in 2003. The year 2007 marked the beginning

[11] We choose the issuer parent provided by DCM Analytics as the relevant hierarchical level. For example, we subsume HSBC Bank plc and HSBC Credit Card Master Note Trust under HSBC Holdings plc.

of the financial crisis, seeing a reduction of liquidity, bank runs and massive downgrades of thousands of structured debt ratings. A dramatic market contraction characterized the following years and by 2011 issuance volumes reached only half the capital collected in 2007. The most complex products, like collateralized debt and loan obligations as well as commercial MBS and structured home equity loans, had almost ceased to exist by the end of 2011. Only the market for residential MBS maintained a high issuance volume.

Figure 2

DCM Analytics also provides the launch ratings by Moody's, Standard & Poors (S&P) and Fitch. We use the standard approach to map Moody's rating scale into those of the other two CRAs ($Aaa = AAA$, $Aa1 = AA+$, ...). Credit ratings below *BBB-* are grouped and labeled as *Junk*. A composite rating is determined for the 15,743 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.[12] Overall, 46% of all securities carry an AAA composite rating and 5% have a *Junk* composite rating, whereas 13% of the securities are not rated by any CRA. Following industry practice, we summarize the different tranche ratings of a deal by the level of AAA *subordination*, which is the fraction of a deal that is not rated AAA. A high AAA *subordination* level signifies a large cushion of subordinated tranches that absorb losses before the AAA-rated senior tranches of the deal are impaired. Fitch allows the lowest AAA subordination levels of 13% on average, followed by Moody's with 21% and S&P with 27%.

Finally, we retrieve coupon information from DCM Analytics. Seventy percent of the 22,359 securities are floating rate notes paying the Libor or Euribor plus a yield spread as a coupon. We winsorize the yield spread at the 2.5% level to account for data errors. The average spread is 89*bp* and has a standard deviation of 104*bp*. We augment the coupon information from DCM Analytics with Libor and Euribor rates from Thomson Reuters Datastream. Bloomberg provides the issuance prices of the securities. The average price paid at issuance as a percentage of the security's face value is 99.8% with a standard deviation of 3.45%. The number of floating-rate notes with the Libor or Euribor as base rate issued at par is 10,625. Furthermore, we use

[12] This procedure is consistent with the "most prevalent institutional rule used for classifying rated bonds" (Bongaerts *et al.* (2012), p.114) and is also used under the Standard Approach of Basel II (BCBS (2006), p. 24).

Bloomberg to retrieve the weighted average live (WAL) of 17,706 securities (mean of 5.6 years) and the currencies in which the securities were issued.

The database Performance Data Services (PDS) provided by Moody's contains credit risk information for 764 European deals in the original sample retrieved from DCM Analytics. The data from PDS comprises the 90-plus delinquency rate defined as the fraction of collateral that is at least 90 days delinquent. The average delinquency rate measured nine months after deal closure is 1.27% and has a standard deviation of 2.18%.[13] We winsorize delinquency rates at the 2.5% level to reduce the impact of data errors. We also use the data on reserve funds and overcollateralization from PDS. (Section 4.3 describes in detail how these variables are used to control for credit risk at the deal level.) Further summary statistics and variable definitions are shown in Tables 1 and 2.

After merging the different data sources we obtain 726 European 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 164 different issuers and carry 6,638 individual tranche ratings. The 1,501 corresponding deal-CRA pairs form the final sample for the regression analyses in Section 5. More details about the sample construction and the use of data filters can be found in the Appendix.

Tables 1 and 2

4 Methodology

An important contribution of this paper is a new market-based method of measuring how favorable ratings are at the deal level. A deal-level measurement is desirable for two reasons. First, deal complexity implies that the exact attribution of interest and amortization cash flows to different tranches can be difficult to identify and simulate. It becomes intractable for a large sample comprising thousands of structured deals. Second, measures of collateral quality and credit enhancement are available at the deal level and cannot easily be related to tranche-level credit risk. Controlling for quality differences across different structured products is best

[13] 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 Appendix for details.

undertaken at the deal level. Therefore, we aggregate tranche ratings to a deal-level rating statistic called *Deal Rating-Implied Spread* ($DRIS$) based on portfolio theory.

In a first step, we infer the market value of different tranche ratings from a linear pricing model. Let y denote the yield spread at issuance of tranche tr in deal d and $\mathbf{D} = (D_{AAA}, D_{AA+}, ...D_{Junk})$ a vector of dummy variables ($D_R \in \{0,1\}$) marking the composite rating of the tranche.[14] 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. It provides a market-based measure of the issuer benefit of obtaining a particular rating in the structured credit market.

In a second step, we interpret a structured deal as a portfolio of its tranches. Let the function $RIS(a, d, tr) : tr \to RIS$ 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 define the *Deal Rating-Implied Spread* ($DRIS$) as

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

The $DRIS$ provides a market-based measure of spread benefits that a set of tranche ratings confers to an issuer, where we assume that the issuer can sell the tranches at the predicted average yields $\widehat{y} = \widehat{\alpha}_D \mathbf{D}$. For example, a rating improvement from AA to $AA+$ for tranche tr implies a decrease in the deal-level credit spread by $\omega_{tr}(\widehat{\alpha}_{AA+} - \widehat{\alpha}_{AA})$. The lower the $DRIS$, the better the overall rating of the structured product. Evidence that credit ratings are highly informative for realized launch spread is provided by Firla-Cuchra (2005) and Ashcraft *et al.* (2011); whereas He *et al.* (2012) provide evidence for a long-run correction of these launch spreads.

The third step of our analysis consists of a deal-level analysis of the determinants of favorable

[14] A composite rating is determined for securities with ratings from more than one CRA. See Section 3.

deal ratings. The $DRIS$ becomes the dependent variable in a linear regression model

$$DRIS(d,a) = \beta_X \mathbf{X}(d,a) + \beta_C \mathbf{C}(d) + \epsilon, \tag{3}$$

where $\mathbf{X}(d,a)$ represents a vector of conflict of interest proxies and $\mathbf{C}(d)$ a set of control variables capturing collateral quality, credit enhancement and issuer fixed effects. The most important explanatory variable for measuring conflicts of interest is the *Agency Specific Securitization Business* ($ASSB$), namely the combined securitization business that an issuer has with any of the three CRAs:

$$ASSB(d,a) := \sum_{tr \in \Omega(d,a)} \mathit{face\ value}\ (tr)\ , \tag{4}$$

where $\Omega(d,a)$ is the set of all tranches rated by CRA a and sold by the issuer of deal d in the issuance year of deal d.[15] $ASSB(a,d)$ proxies the annual amount of rating and consulting fees that the issuer generates for the CRA a that rates deal d. Withdrawing this fee income is the maximal punishment the issuer can inflict upon the CRA and should therefore be a good proxy for the issuer's power to extract more favorable ratings. The extreme positive skewness of $ASSB$ depicted in Figure 3 suggests a log transformation $\mathit{Log}\ ASSB = \ln(ASSB)$ that reduces the skewness to zero.

Section 4.1 presents the pricing model for credit ratings in a unified rating scale. Section 4.2 provides the results of the aggregation of RIS to the $DRIS$ and compares this new measure of deal ratings to the subordination share used in the extant literature. Section 4.3 explains the comprehensive set of control variables $\mathbf{C}(d,a)$, which distinguish the analysis in this paper.

Figure 3

[15] We only consider structured products. This is in line with Mathis *et al.* (2009), who predict conflicts of interest for CRAs whose principal income is generated by rating complex securities. Hau *et al.* (2013) define $ASSB$ similarly but aggregate it over their entire observation period.

4.1 Pricing Credit Ratings

Previous research has established a tight link between credit ratings of structured products and their launch yields.[16] Here we estimate the relationship in equation (1) to obtain the RIS for the tranche ratings using the launch yield spreads of $10,625$ European and North American floating-rate notes (ABS and MBS). All securities have the Libor or Euribor as base rate and were issued at par between 1999 and 2011. Our analysis also has to account for the absence of any rating, which occurs for 14% of all tranches. A non-rating event should convey information as well.[17] Generally, the pricing of non-rated tranches should depend on the rating of the other tranches in the same deal. To illustrate this point, suppose that a deal was structured into two tranches of which one tranche carries a $BB+$ rating while the other tranche has no rating. If the non-rated tranche is subordinated to the $BB+$ rated tranche, then it cannot receive a rating better than $BB+$. Even in the absence of any rating information on the lowest tranche, investors can infer a below $BB+$ *Junk* rating. Similarly, a non-rated tranche where the next more senior rated tranche carries a $AA-$ rating could not have received a rating higher than $AA-$. To capture the signal content conveyed by the absence of a rating for tranches of different seniority, we use three additional rating dummies. First, the dummy *Unrated Junior* equals one for unrated tranches subordinated to another tranche that is itself rated below $BBB-$. Second, the dummy *Unrated Mezzanine/Junior* equals one for unrated tranches where the next more senior *and rated* tranche is rated below AAA but above $BB+$. Third, the dummy *Unrated Senior/Mezzanine/Junior* equals one for all the other unrated tranches.

Table 3

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. The credit risk spread increases roughly monotonically as we move down the rating scale from $AAA+$ to *Junk*. The three dummy variables for non-rated tranches in a deal also behave as expected. In line with the above discussion, the fixed rating effect on the

[16] According to Firla-Cuchra (2005), credit ratings explain 70-80% of launch spreads on European structured debt. See also Adelino (2009), Brennan *et al.* (2009), Kisgen & Strahan (2010), Ashcraft *et al.* (2011) and Chen *et al.* (2012) on the relationship between ratings and prices.

[17] See, for example, Bolton *et al.* (2012).

Unrated Junior dummy exceeds the coefficient on *Unrated Mezzanine/Junior,* which in turn exceeds the coefficient on the *Unrated Senior/Mezzanine/Junior* dummy.

Specifications (2) to (4) in Table 3 refine the rating model by including additional control variables in the yield regressions. Adding fixed effects for the issuance half-year, asset type, collateral nationality and currency, as well as their interaction terms, 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.[18] Column (4) includes in addition two proxies for the shape of the term structure at the time of issuance (Duffee (1998)). *Term Structure Level* represents the 1 month USD Libor rate and measures the level of the term structure, whereas *Term Structure Slope* is the difference between the 12 month USD Libor and the 1 month USD Libor rate and proxies the slope of the term structure. The coefficient on *Term Structure Level* is negative and significant, which is consistent with the extant empirical and theoretical literature. Firla-Cuchra (2005) argues that a higher interest rate level indicates greater profitability in the overall economy. According to Longstaff & Schwartz (1995), a high interest rate level increases the drift of the risk-neutral process for (firm) asset values, which reduces default probabilities; hence spreads vary inversely with interest rates. Consistent with findings by Firla-Cuchra (2005) and Campbell & Taksler (2003), we also obtain a statistically significant negative coefficient on the *Term Structure Slope.* A steep term structure slope anticipates increases in the future short rate, which again correlate with decreasing default risk and default spreads (Collin-Dufresne *et al.* (2001)).

4.2 Deal-Level Aggregation of Rating-Implied Spread

We use the most complete specification in Table 3, column (4) to obtain the *Rating-Implied Spreads* (RIS) as the fixed effects on the rating dummies. This allows us to proceed to the next step of aggregating the RIS to the deal level. Such aggregation presupposes a translation of the rating scale into a cardinal yield spread measure. According to standard portfolio theory, the credit spread on the portfolio of deal tranches is just the asset-weighted average RIS of

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

all tranches as expressed in equation (2). For example, a deal with two equally large tranches rated A and BBB with corresponding credit spreads $RIS(A) = 26.4bp$ and $RIS(BBB) = 78bp$ implies an aggregate credit risk spread $DRIS = 0.5(26.4 + 78)bp = 52.2bp$. If a second CRA rates the second tranche better at $BBB+$ (instead of BBB), then its deal-level credit spread assessment is lower at $DRIS' = 0.5(26.4 + 71.8)bp = 49.1bp$ because $RIS(BBB+) = 71.8bp$. This example also illustrates how the $DRIS$ can vary across rating agencies for the same deal.

While the aggregation of the RIS is generally straightforward, two special issues may arise. First, issuers may not publish ratings for all the tranches of a deal. In such cases we resort to the rating dummies labeled *Unrated Junior*, *Unrated Mezzanine/Junior* and *Unrated Senior/Mezzanine/Junior* (explained in the previous section). However, if a CRA has not rated *any* tranche of a particular deal, we do not compute a $DRIS$ for the respective deal-CRA pair and exclude the respective observation from the analysis. Second, issuers may not securitize and sell all tranches of a deal, but instead retain the so-called "equity tranche" that ranks lowest in seniority. The average size of this unsecuritized junior part of a deal is on average 1.5% of the deal face value. We generally include the unsecuritized tranches in the computation of the $DRIS(d, a)$ because controls for collateral quality and credit enhancement extend to it as well. In particular, we apply the RIS of the *Unrated Junior* dummy in Table 4, column (4) to these retained equity tranches. Robustness checks in Section 6 document that this procedure is not critical to the results of our analysis. Neither ignoring the unsecuritized part of a deal completely nor charging the even higher RIS implied by a $Junk$ rating qualitatively changes the findings.

The previous literature has used the level of AAA subordination as a proxy of how favorable tranche ratings are to an issuer (Ashcraft *et al.* (2010), He *et al.* (2011)), where the AAA subordination is simply defined as the fraction of a deal rated below AAA. Such a crude aggregation rule is a much less informative deal rating statistic than *DRIS*. Figure 4 compares the AAA subordination share in our data sample to the $DRIS$ computed under our aggregation method by plotting the former on the x-axis and the latter on the y-axis. A correlation of 0.55 indicates that issuers pay higher *DRIS* for deals with a large share rated below AAA. However, the scatterplot also reveals that deals with the same level of AAA subordination often exhibit very different *DRIS* values. The level of AAA subordination disregards the information conveyed by the different ratings that the subordinated tranches of a deal have received instead of a AAA rating. By contrast, *DRIS* account for the large spectrum of rating scales below AAA providing for a much more accurate deal rating statistic.

Figure 4

Table 2 provides summary statistics for all $DRIS$ as well as for individual CRAs. The largest number of deal ratings is obtained for S&P (5,655 observations) followed by Moody's (5,196) and Fitch (3,561). The average *DRIS* is largest for S&P with an average credit spread of 14*bp* compared to 12*bp* and 8*bp* for Moody's and Fitch, respectively. The extreme positive skewness of the $DRIS$ depicted in Figure 3 suggests a log transformation *Log* $DRIS = \ln(DRIS + 0.0024)$, which brings the skewness to zero in the final data sample used in the empirical analysis. All subsequent regression analysis is based on this log transformation of the $DRIS$, which has a mean of -4.3 and a standard deviation of 2.1.

4.3 Controlling for Credit Risk

Cross-sectional variation in the aggregate deal rating should vary with the credit risk of a deal. Different issuers might have access to collateral pools of different quality. It is therefore important to control for the credit risk embodied in a securitization deal. The following section explains the credit risk controls given by

$$\mathbf{C}(\mathbf{d}) = \{\textit{Log Delinquency, Log Delinquency Squared, Deal Fraction with Guarantee,}$$
$$\textit{Overcollateralization, Reserve Fund, Number of Tranches, Collateral Type/Nationality}\}.$$

The quality of the collateral pool backing a structured product should be a prime determinant of credit risk. As an *ex post* proxy of collateral pool quality, we use the cumulative delinquency rates measured over the first nine months after deal closure. Our definition of delinquency is the so-called "90plus" criterion, which requires an asset to be at least 90 days in delinquency to be counted as such. Yet delinquency definitions and their reporting might differ somewhat across various collateral classes. We use additional collateral-type fixed effects to control for such differences as much as possible. Fixed effects for the half-year and for the national origin of the collateral are also included.

Because of positive skewness and kurtosis of the delinquency statistics (see Figure 3), we winsorize 2.5% of each tail and apply the log transformation *Log Delinquency* = ln(*Delinquency* + 0.0045) to obtain zero skewness. To account for possible non-linearities in the relationship between *Log Delinquency* and $DRIS$, we also include *Log Delinquency Squared* as an additional credit risk proxy. Table 2 provides summary statistics about the delinquency measures as well as the other control variables.

Credit enhancement reduces the credit risk of a deal for any given collateral quality through the use of overcollateralization, liquidity reserves and bond insurance. *Overcollateralization* is measured as the difference between the total collateral asset principal value and the combined principal value of the deal tranches standardized by the combined tranche principal. The issuers may 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 deal-specific size of the *Reserve Fund* is standardized by the combined tranche principal. We ensure that *Overcollateralization* and *Reserve Fund* are measured within six months after deal issuance. After eliminating all deals without credit enhancement information within this time window, and after excluding all deals without delinquency data, there remain 764 European deals or approximately 10% of the deals originally provided in the DeaLogic database. The mean of *Overcollateralization* is -2% so that the average deal is in fact slightly *under*collateralized. The average *Reserve Fund* equals 3%. Besides overcollateralization and liquidity reserves, bond insurance represents a third form of credit enhancement. The data provided by DCM Analytics allows us to construct the control *Deal Fraction with Guarantee*, defined as the aggregate principal value of the deal tranches that benefit from debt insurance standardized by the size of the deal. This variable captures direct guarantees given by either an external party or by the issuer itself. Approximately 7% of the average deal benefits from bond insurance. Issuer fixed effects control for any *implicit* promises of liquidity or credit support that investors and CRAs might expect from the issuer of a deal. The issuer fixed effects also capture differences in the reputation and creditworthiness of the issuers.

Unlike collateral quality and credit enhancement, the design of deal structures should not alter the overall credit risk at the deal level. Yet the optimal design of deal structures might itself *respond* to collateral quality and credit enhancement, so that it becomes an additional measure of credit risk. For example, more risky collateral might entice issuers to segment credit risk into more tranches so that the deal structure becomes more complex. We therefore include the *Number of Tranches* as a control variable. The median number of tranches is two, but 10% of all deals have seven or more tranches.

5 Empirical Analysis

5.1 Evidence from Subordination Levels

The previous literature has identified low levels of AAA subordination as indicative of rating favors. 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 non-parametric analysis by checking if a CRA gives an AAA rating to a larger share of a deal if the issuer is among its most important customers in the securitization market.

Table 4 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 Agency-Specific Securitization Business ($ASSB$) aggregated over the period 1999–2011. The average deal share of subordinated tranches across all deals rated by Moody's is 21%. By contrast, the average subordination level that Moody's allows its 10% largest clients is only 13% and for the top 5% of clients it even drops to 11%. The result extends qualitatively to subordination levels granted by S&P and Fitch. On average, deals issued by the 10% or 5% most important customers benefit from lower AAA subordination levels. A Wilcoxon rank-sum test compares the deals of the 10% (5%) top issuer clients against the deals of the remaining 90% (95%) smaller 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.[19]

The largest issuers might have access to collateral that is of higher quality and that would justify lower AAA subordination levels. We analyze the deals for which we have delinquency

[19]The high values of the standardized test statistics in columns (3), (6) and (9) confirm that the deals of those issuers that generate most rating business receive significantly lower AAA subordination levels. The standardized test statistic is approximately normally distributed in large samples.

data to check the validity of this hypothesis. For deals rated by S&P and Fitch, roughly 1.5% of all collateral is at least 90 days delinquent nine months after deal closure. By contrast, the average delinquency rate only for the deals of the top 5% customers exceeds 2%. The rank-sum test confirms that the top 10% (5%) issuer clients of S&P and Fitch structure collateral of significantly lower quality than the 90% (95%) smaller issuers. In the case of Moody's significant differences are detected between the deals of the 10% largest and the 90% smallest clients.

Next we compare the amount of credit enhancement across issuer clients and CRAs. On average the deals of the CRAs' largest issuer clients benefit from more bond insurance, which would justify lower AAA subordination levels. However, the differences are not statistically significant. Neither are we able to detect any significant differences between large and small issuers for deals with data on liquidity reserves. The average deal of the CRAs' top 10% (5%) clients tends to benefit from higher overcollateralization levels than the deals of small issuers. However, even these deals remain slightly *under*collateralized. A statistically significant feature shared by the clients of all three CRAs concerns the size and structure of deals. The 10% (5%) largest issuers sell larger deals tranched into fewer securities.

In summary, Table 4 suggests that CRAs grant significantly lower AAA subordination levels to their most important clients although delinquency rates and credit enhancement levels do not suggest that these deals are less risky. However, the non-parametric analysis suffers from at least two shortcomings. First, it only compares the distribution of AAA subordination levels and deal characteristics in two different samples without controlling further for deal heterogeneity. Second, the AAA subordination share is a very crude statistic for how favorably the tranches of a deal were rated—an aspect highlighted in Figure 3 by the loose relationship between AAA subordination and the *DRIS* measure, which is examined further in the next section.

Table 4

5.2 Evidence from Deal Rating-Implied Spreads (*DRIS*)

In this section we estimate the model specified in equation (3), which uses the deal rating statistic $DRIS(d,a)$ from Section 4.2 as the dependent variable (in log). $DRIS(d,a)$ represents the average yield spread implied by the credit ratings from CRA a for all tranches of deal d. A deal with a high $DRIS(d,a)$ value has received low credit ratings for its tranches. A key explanatory variable in Table 5 is the (log) Agency-Specific Securitization Business *Log* $ASSB(d, a)$ shared between CRA a and the issuer of deal d. Hypothesis 1 predicts that deals with a high $ASSB$ receive better ratings and hence lower $DRIS$.

The regression coefficients of the controls $\mathbf{C}(d)$ in Table 5 have the expected signs. In all specifications, deals with a high delinquency rate nine months after deal closure have lower ratings, implying significantly higher deal spreads $DRIS$. The regression coefficients on *Deal Fraction with Guarantee*, *Overcollateralization* and *Reserve Fund* are all negative. Deals with higher credit enhancement tend to have better ratings, which imply lower spreads; yet only the coefficient on *Overcollateralization* is also statistically significant. In all specifications the coefficient on *No. of 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.[20]

The fixed effects for collateral nationality and time feature (unreported) joint p-values of zero and represent useful control variables. The additional inclusion of issuer fixed effects (columns (2) to (4)) raises R^2 from 30% to 57% and suggests that issuer characteristics like creditworthiness, reputation or management skills may be important determinants of structured debt ratings. They seem to explain a higher variation of $DRIS$ than explicit debt insurance proxied by *Deal Fraction with Guarantee* and featuring a statistically insignificant coefficient.

The key regression coefficient on *Log* $ASSB$ is statistically significant and negative in all specifications. Issuers who generate more rating business receive better overall tranche ratings captured by lower deal rating-implied spreads. In column (2) the coefficient is significant at the 1%-level although standard errors are clustered both by deal and by issuer and issuer fixed effects are included. The coefficient value of -0.255 implies that an increase of *Log* $ASSB$ by two standard deviations ($2 \cdot 1.47$) translates into a reduction in $DRIS$ by 75%. This corresponds to a spread reduction of 9*bp* for a representative deal with an average $DRIS$ of 12*bp*.[21]

[20] Although a high number of tranches is associated with lower ratings (higher *DRIS)*, investors may still require lower *overall* spreads on more complex deals. When included as a control in the pricing model of Section 4.2, *No. of Tranches* takes a negative (though insignificant) regression coefficient. In a group of securities *with identical ratings*, the securities from deals with many tranches tend to sell at lower spreads.

[21] Two standard deviations in *Log* $ASSB$ are 2.94 (see Table 2). Since our dependent variable is the log of $DRIS$, an increase of *Log* $ASSB$ by 2.94 decreases $DRIS$ by $2.94 \cdot 25.5\% = 75\%$. According to Table 2, the average $DRIS$ over all deal-CRA pairs is 12*bp* and a decrease of 75% corresponds to 9*bp*.

We also explore whether issuers obtain better ratings for larger deals. Larger deals might 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 5% level. Yet including both the conflict of interest proxy *Log ASSB* and the *Log Deal Face Value* in column (4) shows clearly that the former is the relevant explanatory variable, while the latter becomes statistically insignificant.

Table 5

5.3 Rating Bias by Deal Quality and Asset Type

Next, we explore whether the conflict of interest might be heterogeneous across the distribution of deal quality, as stated in Hypothesis 2. In particular, we conjecture that low-quality structured deals might have benefited from larger rating favors as they tend to be more profitable to the issuer than rating favors on already highly rated deals. Table 6, columns (2) to (6), shows the results of simultaneous quantile regressions for the 10%, 25%, 50%, 75% and 90% quantile, respectively.[22] For comparison, column (1) displays the OLS results of Table 5, column (1).

Table 6

The regression coefficients for *Log ASSB* are negative and statistically significant at the 1% level for all quantiles. Yet the coefficient is most negative at the 90% quantile. Figure 5 plots the coefficient on *Log ASSB* against different quantiles. Up to the 70% quantile the coefficient appears roughly constant at levels between -0.10 and -0.15 before dropping steeply to -0.238 at the 90% quantile. An F-test using the between-quantile blocks in the variance-covariance matrix calculated during the simultaneous quantile regression assesses differences between the *Log ASSB* coefficients calculated at different quantiles.[23] One-sided p-values are below 5% for the 50% and 75% quantile and below 10% for the 10% and 25% quantile.[24]

[22] Issuer-fixed effects are ignored to reduce computing time for bootstrapped standard errors.

[23] We use the Stata command *sqreg* for simultanous-quantile regression. See Stata help and http://www.stata.com/stb/stb38/sg70/sqreg.hlp for documentation.

[24] The F-statistic has one degree of freedom in the numerator and 1,447 degrees of freedom in the denominator. It thus equals the squared t-statistic with 1,447 degrees of freedom for which one-sided p-values can be computed under the null hypothesis H0: Coefficient at Q(90) $\geq$ Coefficient at Q(x).

Figure 5

Deals beyond the 90% quantile have a $DRIS$ of more than $29bp$ which exceeds the rating-implied spread of an A- rating. Hence, relatively large parts of deals beyond the 90% quantile must have received ratings below A- (mezzanine and junior tranches). Figure 5 suggests that agency conflicts are particularly pronounced for these most risky deals. At the 90% quantile of the $DRIS$ distribution ($29bp$), an increase of $Log\ ASSB$ by two standard deviations is associated with an economically large spread reduction of $20bp$.[25] Consistent with the first part of Hypothesis 2, issuer incentives to lobby for rating favors are stronger for very risky deals as investors require very high spreads for securities rated below A-. This result extends to different asset types. The deals with the 10% highest $DRIS$ values in the sample used for the quantile regressions comprise both MBS (57%) as well as ABS deals (43%).

The second part of Hypothesis 2 predicts more pronounced rating favors for ABS than for MBS deals. The first tend to have more opaque deal structures and are therefore harder to rate. The average ABS deal is tranched into 4 securities as opposed to the average MBS deal with only 2.7 tranches. A Wilcoxon rank-sum test rejects the null hypothesis that the *No. of Tranches* is identically distributed for ABS and for MBS deals. In addition to more opaque deal structures, ABS deals also tend to be riskier than MBS deals which receive better credit ratings on average. A rank-sum test rejects the hypothesis that the $DRIS$ has the same distribution for ABS and for MBS deals in our full sample with 14,412 deal-CRA pairs.[26]

Table 7

As ABS deals tend to be riskier and more complex, we predict more pronounced rating favors for them than for MBS deals. Table 7 reports regression coefficients that were estimated separately for the MBS subsample (columns (1) and (2)) and for the ABS subsample (columns (3) and (4)). The coefficient of $Log\ ASSB$ is highly significant for ABS *as well as* MBS deals despite smaller sample sizes and even when (log) deal size is controlled for. Furthermore, we observe a larger $Log\ ASSB$ coefficient in the ABS than in the MBS sample, as Figure 6 illustrates. The graph plots the regression residuals $Log\ DRIS - \widehat{\beta}_C\mathbf{C}$ of specifications (1)

[25] $2 \cdot 1.47 \cdot 0.238 \cdot 29bp = 20bp$

[26] However, the same test cannot reject the null hypothesis in the smaller sample, which has 1,501 deal-CRA pairs and which is used in the regression analyses.

and (3) against the *Log ASSB*. The slope of the black regression line for ABS is -0.389 and much steeper than the slope of the red regression line of -0.275 for the MBS sample. While large issuer clients with high *ASSB* receive rating favors for ABS as well as MBS deals, the conflict of interest seems to be more pronounced in the ABS sample. However, the regression coefficient of an interaction term between *Log ASSB* and a dummy variable for ABS deals is not significant when estimated in the full sample comprising ABS as well as MBS deals (columns (5) and (6)).

Figure 6

5.4 Conflicts of Interest over the Credit Cycle

The incentives for CRAs to grant rating favors are presumably stronger during credit booms when default probabilities and reputation costs of ratings inflation are relatively low (Hypothesis 3). Issuers that generate a lot of rating business are predicted to receive particularly inflated ratings during the structured debt boom from 2004 to 2006. By contrast, rating favors should be less pronounced during the financial crisis when risk-aversion, perceived uncertainty and default probabilities were high. To test this hypothesis, we define the credit boom dummy *Issued 2004-06* and the crisis dummy *Issued 2007-08* and interact them with the conflict of interest proxy *Log ASSB*. 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 8, column (1), reports the regression coefficients of the two interaction terms. As time-fixed effects are already controlled for, the boom and the crisis dummy are not included separately.

As Hypothesis 3 predicts, issuers that generate a lot of rating business receive larger rating favors during the credit boom. The coefficient on the interaction *Issued 2004-06* $\times$ *Log ASSB* is negative and highly significant. The coefficient on *Log ASSB* alone becomes statistically insignificant suggesting that agency problems can, to a large extent, be attributed to the credit boom period alone. The coefficient on the interaction term for the financial crisis is statistically insignificant, suggesting that CRAs stopped granting rating favors when financial stress increased in 2007. This observation is also consistent with the massive downgrades that took place in 2007 and 2008 (Benmelech & Dlugosz (2009b)).

Table 8

5.5 Ratings Shopping over the Credit Cycle

Hypothesis 4 states that issuers suppress low credit ratings during credit booms when investors are less risk averse and the value of publishing a second or third rating is low. The ratings of a CRA that survives ratings shopping should thus be better than the ratings of deals that have been shopped less aggressively and that carry ratings from several CRAs (winner's curse). During the credit boom single-rated deals are expected to have lower $DRIS$ (better ratings) than deals with ratings from several CRAs. To test this prediction we define the dummy variable *Single CRA*:

$$\textit{Single CRA}\ (d) := \begin{cases} 1, & \textit{if all tranche ratings of deal } d \textit{ are from the same CRA} \\ 0, & \textit{else} \end{cases} \tag{5}$$

Table 8, specification (2), includes *Single CRA* and its interactions with the boom and the crisis dummies defined in the previous section. The coefficient on *Single CRA* is positive and significant at the 5% level and the interaction term *Issued 2007-08* × *Single CRA* is statistically insignificant. In normal times and during the crisis, deals with ratings from only one CRA had *higher* $DRIS$ (lower ratings). Outside credit booms, issuers publish multiple opinions from several CRAs to reduce lemon discounts for their high-quality deals. Only the risky deals that do not suffer from adverse selection carry ratings of just one CRA. These single-rated lemon deals have on average worse ratings.

The coefficient on the interaction term *Issued 2004-06* × *Single CRA* is negative, significant at the 5% level and exceeds the coefficient on *Single CRA* in absolute terms. During the credit boom the ratings of single-rated deals have on average better ratings and hence lower $DRIS$. This result suggests that issuers suppressed bad ratings in exactly the same years (2004 to 2006) that are also characterized by deliberate ratings inflation (Section 5.4).[27] The simultaneous appearance in the lead-up to the financial crisis is consistent with a causal rela-

[27] Benmelech & Dlugosz (2009b) collect evidence that ratings of single-rated deals are on average inflated. Their identification strategy relies on the idea that inflated ratings should perform worse ex-post than unbiased ratings. Consistent with ratings shopping, the authors find that "tranches rated solely by one agency (...) were more likely to be downgraded by January 2008 (...) more likely to suffer more severe downgrades."

tionship between ratings shopping and rating favors. The threat to suppress an unfavorable rating could have increased competitive pressure on strict CRAs to reduce the rating distance to more accommodating competitors (Griffin *et al.* (2013)).

6 Robustness Checks

6.1 Heterogeneity across Credit Rating Agencies

In this section we check whether our results are driven by CRA fixed effects, which might 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 the risk assessment of Moody's 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 might be intended to imply a different default rate than an AAA rating by Fitch. Table 8, column (3), controls for such CRA fixed effects and finds that they are statistically insignificant.

Next we analyze if the sensitivities to *Log ASSB* differ across CRAs. Column (4) includes CRA dummies as well as their interactions with *Log ASSB*. The coefficient on $Log\ ASSB$ itself remains negative and highly significant. Therefore, we are confident that the results uncovered in Section 5.2 are not solely driven by one single CRA that might only rate the deals of large issuers and produce generally better ratings than other CRAs. Instead, the three CRAs all accord better ratings to issuers with which they share a large *ASSB*.

Nevertheless, the regression coefficients on the CRA dummies and their interactions with Log ASSB 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 agency conflicts.

We find that S&P seems to be as strict as Moody's when rating favors are controlled for. Similarly, S&P does not grant statistically more pronounced rating favors than Moody's. By contrast, the coefficient on the Fitch dummy is large and significant. Hence, if rating favors by Fitch are controlled for, then Fitch appears to attribute stricter ratings than Moody's. At the same time, the interaction term *Fitch* × *Log ASSB* is negative and highly significant, suggesting that agency conflicts are more pronounced for Fitch. *One* possible explanation could be that Fitch was competing on rating favors to strengthen its market position. Fitch produced only 24% of all ratings in our data sample (1999–2011) whereas Moody's accounts for a market share of 36% followed by S&P with 40%.

6.2 Alternative Portfolio Models for *DRIS*

In the portfolio model of Section 4.2, rating-implied spreads of different tranches were aggregated to deal level. Unsecuritized and hence unrated equity tranches were charged with the RIS implied by *Unrated Junior*. This section analyzes whether our main results are robust to alternative ways of treating the unsecuritized junior tranches of deals.

In Table 9, columns (1) and (2), *Log* $DRIS$ are again regressed on *Log* $ASSB$. However, the unsecuritized part of a deal is ignored in the computation of $DRIS$. The asset weights ω_{tr} of the *securitized* tranches in equation (2) are now computed considering only *securitized* deal tranches. In columns (3) and (4) we take the opposite approach. Instead of ignoring the unsecuritized part of a deal completely, we charge it the RIS implied by a *Junk*-rating. Hence, whereas the first two specifications in Table 9 charge the average RIS received by securities in our sample, columns (3) and (4) charge the highest possible rating-implied spread for the unsecuritized part of a deal.

We find that the regression coefficient on *Log ASSB* remain significant in the first four columns. Our main results are robust to different specifications of the $DRIS$ portfolio model.

Table 9

6.3 Rating Favors Priced into Yield Spreads

The deal rating statistic $DRIS$ is based on market values of credit ratings. It aggregates rating-implied spreads RIS defined as the fixed effect capturing the average launch spread of tranches with the same rating. A potential drawback of this market-based rating measure concerns the pricing of rating favors. Sophisticated investors could anticipate conflicts of interest and demand higher spreads for securities with potentially inflated credit ratings. In this case the estimated RIS and hence our deal rating statistic $DRIS$ would include a risk premium for rating favors.

To account for market pricing of deliberate ratings inflation, we reestimate the full RIS-model but control for the annual securitization business that the issuer of a security generates for the rating industry. Equation 1 becomes

$$y = \alpha_D \mathbf{D} + \alpha_Z \mathbf{Z}_{tr} + a_{SB} \cdot Log\ SB + \epsilon, \tag{6}$$

where $Log\ SB$ is the (log) annual securitization business generated by the issuer. SB is defined like the $ASSB$ except that it is not agency-specific but includes the face values of securities rated by *any* of the three CRAs. The reason for considering SB rather than the agency-specific $ASSB$ is that our RIS-model is estimated for 13 *composite* rating dummies and not for *agency-specific* ratings, in which case 39 different rating dummies would have been required.

We estimate the model specified in equation 6. The regression coefficient on $Log\ SB$ is -0.008 and its t-statistic is only 1.18. We also include the interaction of $Log\ SB$ with a credit boom dummy, as rating favors were shown to be most pronounced in the period from 2004 to 2006 (Section 5.2). But the regression coefficient on this interaction *Issued 2004-06* $\times$ *Log SB* is also small (-0.005) and statistically insignificant. Therefore, we find no evidence that the risk of rating favors is priced into the launch yields of structured debt securities. Nevertheless, we compute new $DRIS$ values, using the model specified in equation 6, and then repeat the base line regression of Section 5.2 to test our Conflict of Interest Hypothesis. Table 9, columns (5) and (6), shows the new regression coefficients. The differences from Table 4 are marginal. The business relationship between issuer and CRA remains an economically and statistically important determinant of rating favors.

6.4 Regression based on AAA Subordination

Ashcraft *et al.* (2010) and He *et al.* (2011) use *AAA subordination*—the deal fraction that is subordinated to the AAA tranches—as a summary statistic of a deal's tranche ratings. In this section we check if our results for Hypothesis 1 are robust to the use of *AAA subordination* instead of $DRIS$.

As *AAA subordination* is heavily skewed and leptokurtic (Figure 3), the logarithmic transform *Log(AAA subordination + 0.0075)*, which reduces the skewness to zero, is used instead. The regression coefficients on *Log ASSB* in Table 9, columns (7) and (8), are negative, significant and large in absolute terms. An increase of *Log ASSB* by two standard deviations decreases the deal fraction that is subordinated to the AAA tranches by roughly 51%.[28] Issuers that generate a lot of rating income receive AAA ratings for larger deal parts, which is consistent with Hypothesis 1.

7 Conclusion

Credit ratings are supposed to reduce informational asymmetries in the financial industry. But rating favors lower the accuracy of credit risk information, thereby distorting investment decisions and redistributing resources from disadvantaged borrowers to security issuers with a larger business interest for CRAs. Furthermore, ratings inflation relaxes rating-contingent regulatory constraints with negative implications for financial stability.[29] The importance of accurate credit ratings for efficient capital allocation and financial regulation calls for research on conflicts of interest that potentially distort rating processes.

We contribute to this research in two ways. First, we develop a new methodology to compare credit ratings in structured debt markets whose complexity otherwise challenges empirical analysis. Our Deal Rating-Implied Spread $DRIS$ summarizes tranche ratings to deal level based on market values of credit ratings. Importantly, $DRIS$ is independent of the specific intra-deal allocation of credit risk but still accounts for the detailedness of rating scales which a crude deal measure like the level of AAA subordination cannot pick up. Second, our methodology allows us to uncover conflicts of interest in credit rating transactions for European asset and mortgage backed securities controlling for a large set of credit risk determinants.

In a cross-section of 1,501 deal-CRA pairs we find that deals receive better credit ratings if the CRA has a large business interest in the deal issuer. An increase of the business volume between the CRA and the issuer by two standard deviations reduces the issuer's financing costs by on average $9bp$. This structural relationship between the size of an issuer's securitization business and the rating favors received necessarily leads to competitive distortions that foster issuer concentration.

[28] $2 \cdot 1.47 \cdot 17.4\% = 51\%$

[29] According to Hunt (2009) ratings played a role in at least 44 SEC rules as of June 2008. Also quasi-regulatory constraints often rely on the quality of credit ratings. Cantor *et al.* (2007) find that 75% in a survey of 200 pension plan sponsors and investment managers have rating requirements.

We also uncover heterogeneity of agency conflicts across the distribution of deal quality. Rating favors are twice as large for the 10% of deals with the largest rating-implied credit risk. An increase of the business volume between CRA and issuer by two standard deviations corresponds to a rating favor of 20*bp* for the most risky deals with large junior and mezzanine tranches. The fact that the ratings of these credit risk lemons were particularly distorted poses a threat to financial stability because it creates incentives to supply more and more low quality products to the market. This incentive distortion can explain the observed quality degradation over the structured credit boom, which was not accompanied by the issuance of stricter credit ratings (Ashcraft *et al.* (2010)).

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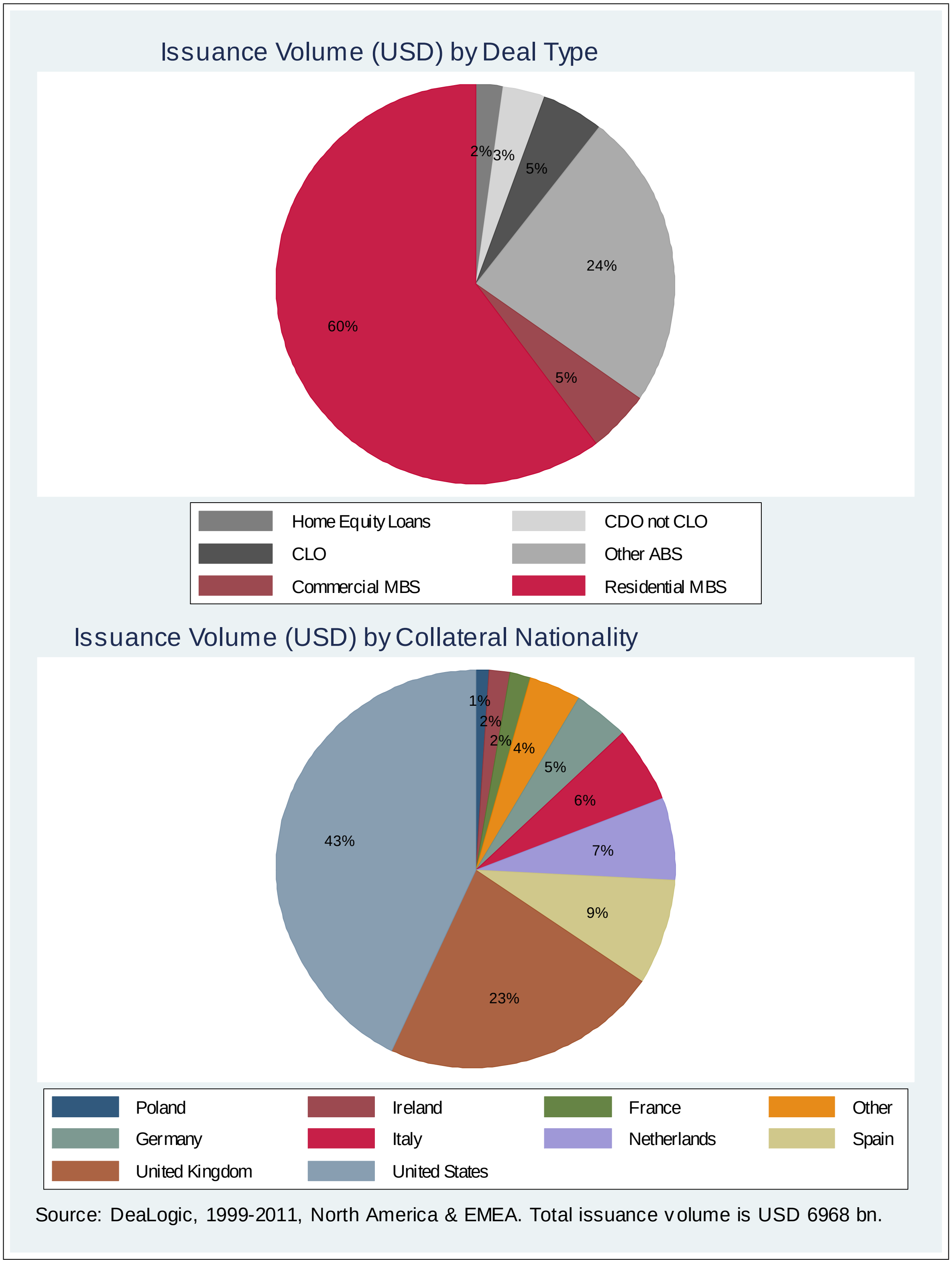

Figure 1: The structured debt market is decomposed into different collateral types and national origins of the collateral. The issuance volume is computed as the total principal value in USD of all securities with an ISIN identifier issued between 1999 and 2011.

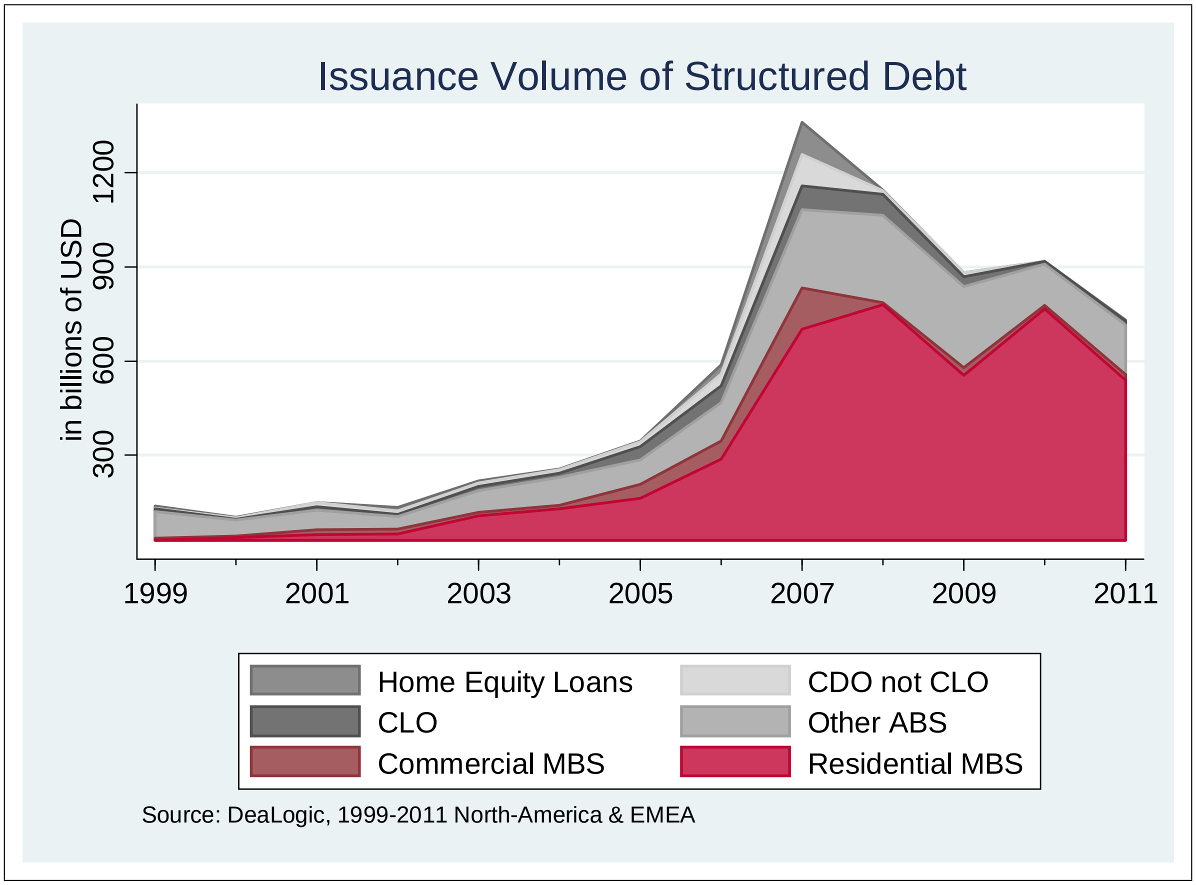

Figure 2: The market growth of structured debt between 1999 and 2011. The issuance volume is computed as the total principal value in USD of all securities with an ISIN identifier issued between 1999 and 2011.

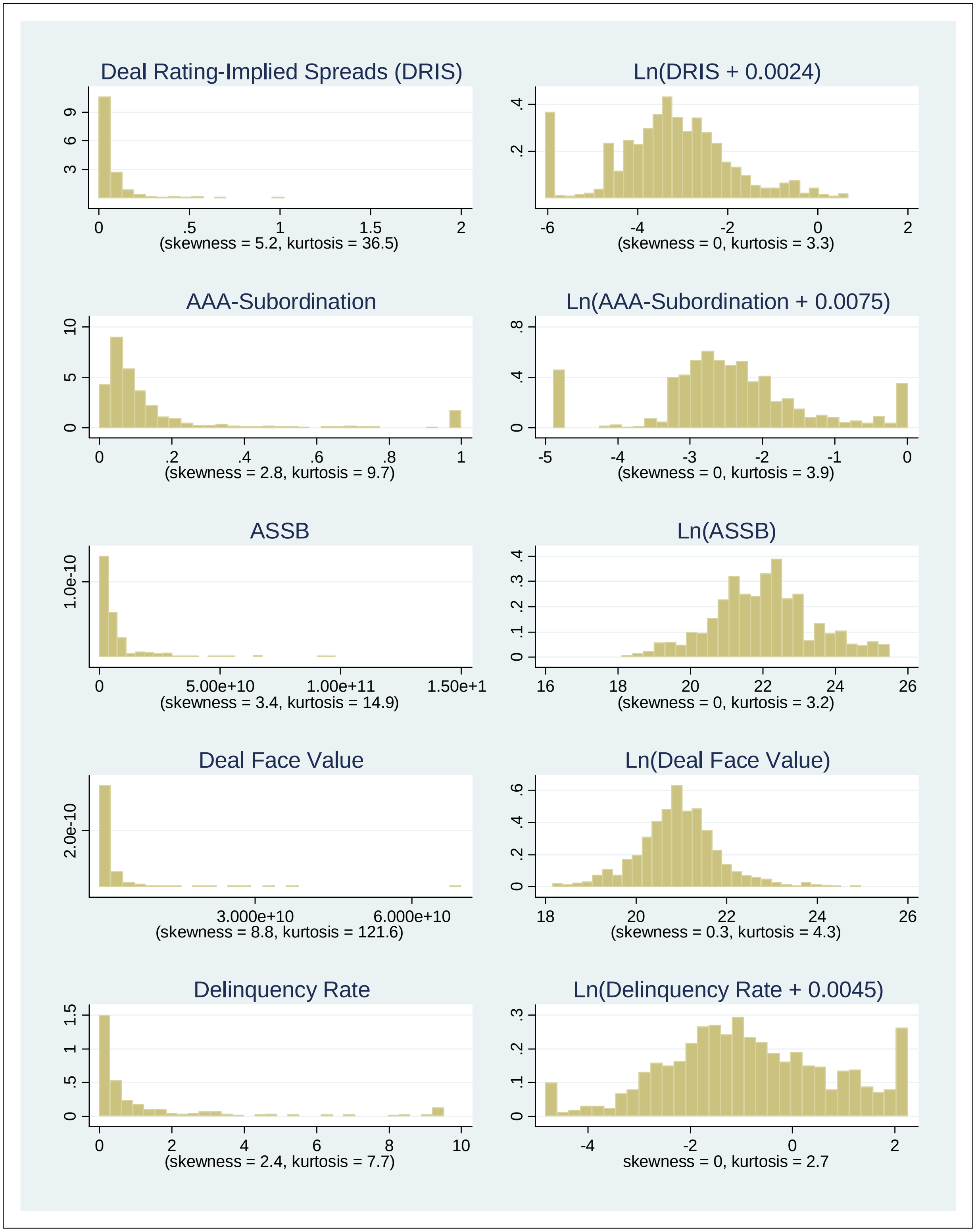

Figure 3: Histograms for *DRIS*, *AAA Subordination*, *ASSB*, *Deal Face Value* and *Delinquency Rate* before and after their log transformation. The histograms are drawn for the final data sample with 1501 deal-CRA pairs (726 deals) used in the regression analysis.

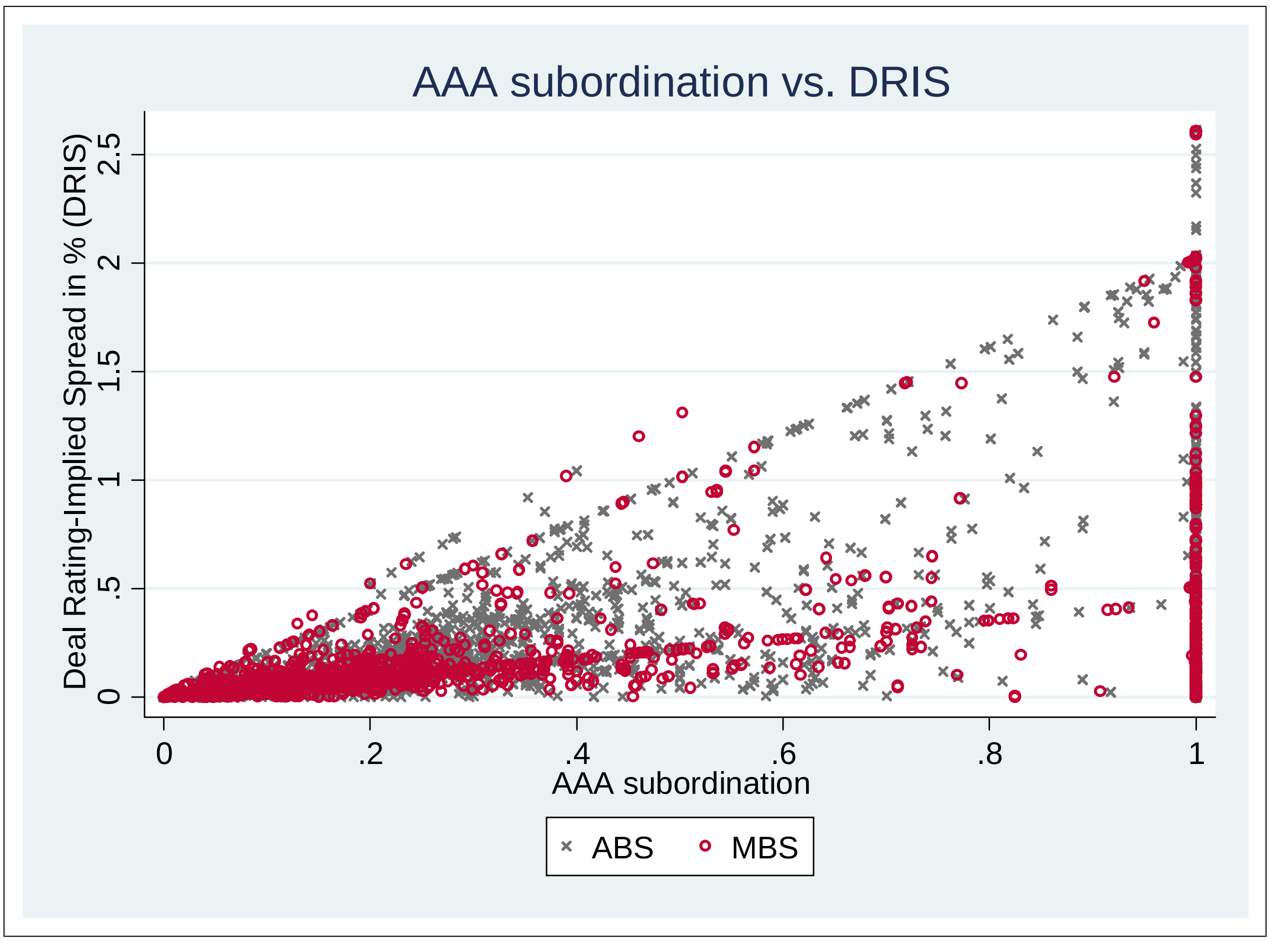

Figure 4: Alternative Deal Rating Statistics: *Deal Rating-Implied Spread* (*DRIS*) is plotted against *AAA subordination* for 13,383 deal-CRA pairs (d, a).

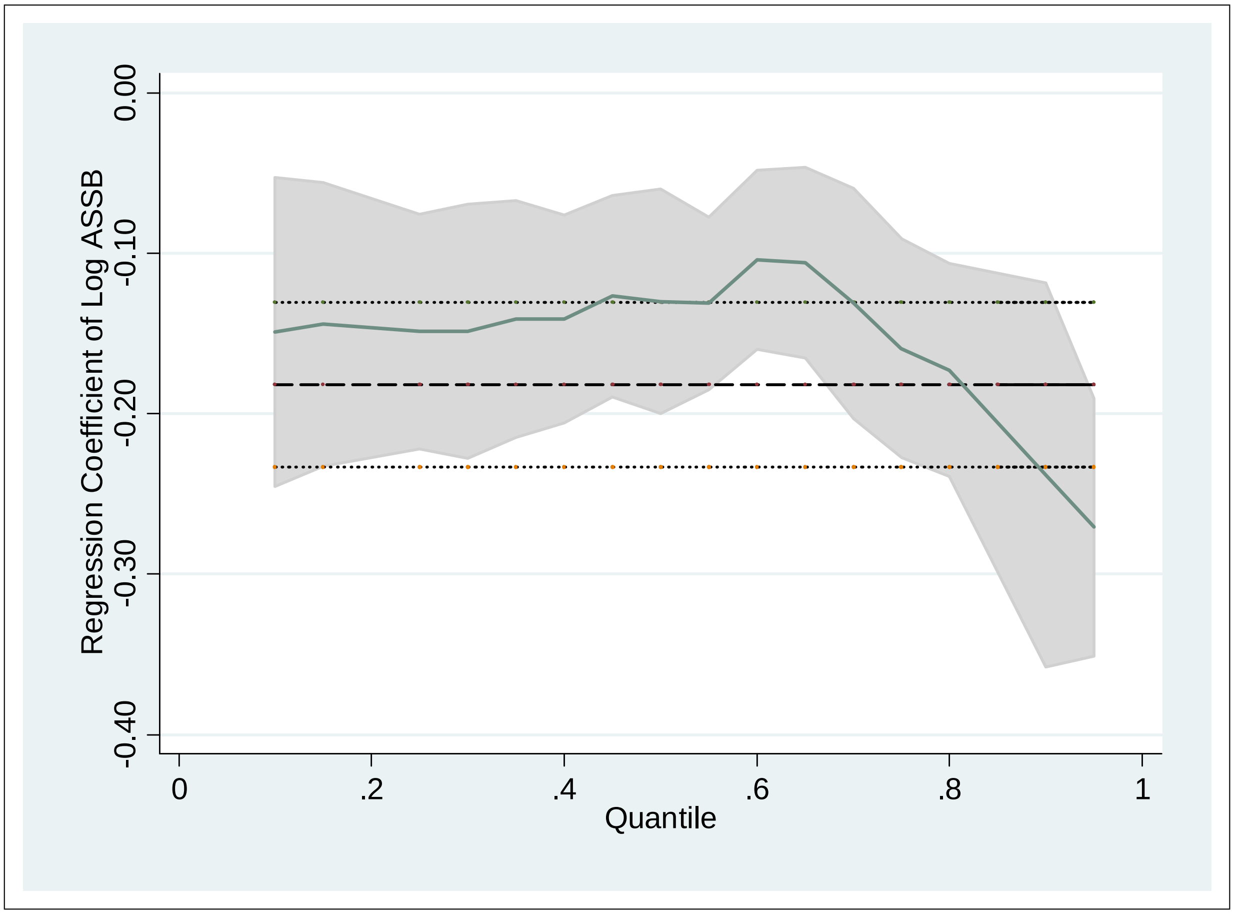

Figure 5: Rating Favors by Deal Quality: The coefficient of *Log ASSB* is estimated in multiple quantile regressions and plotted against the corresponding quantiles of *Log DRIS*. Confidence intervals are computed for the 5% level. The bold dashed line represents the OLS-coefficient of *Log ASSB* in Table 4, column (1).

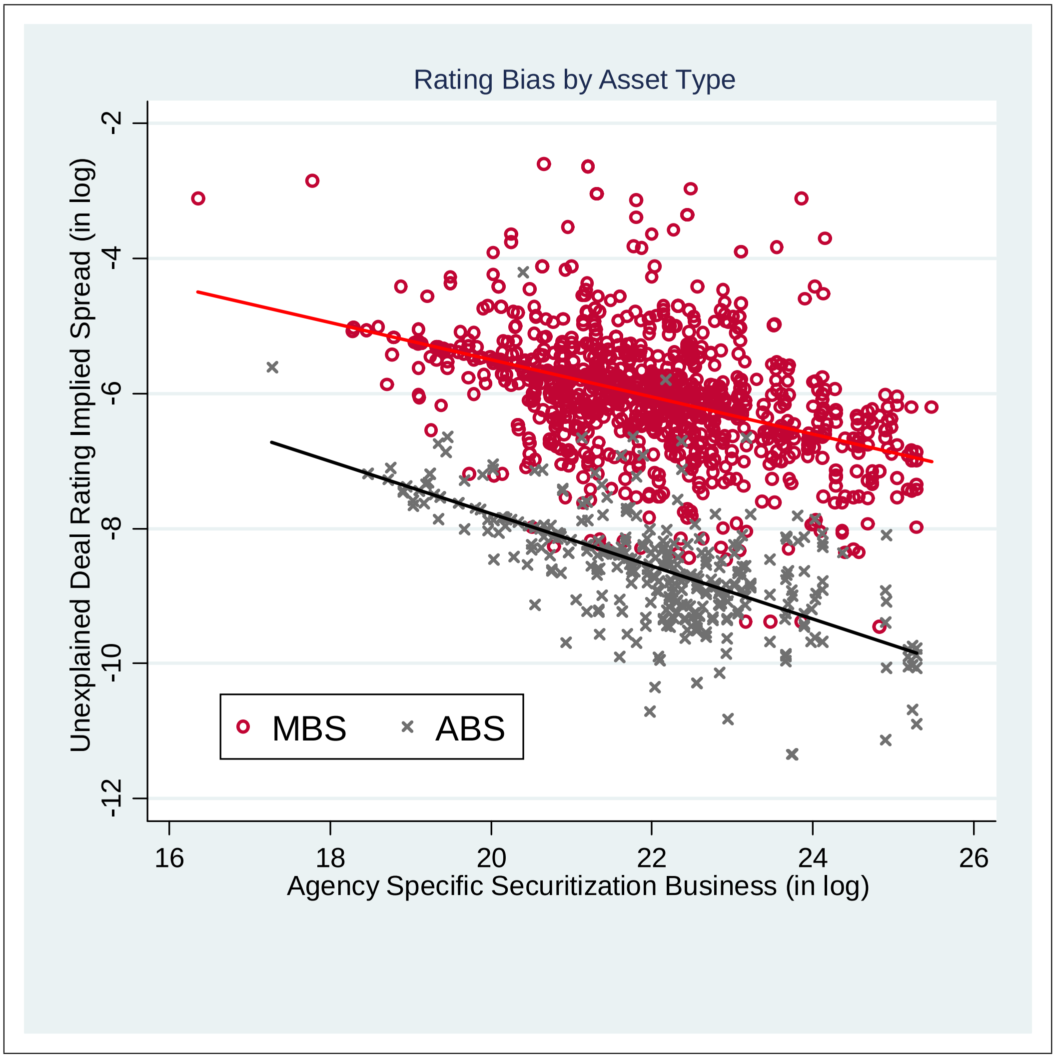

Figure 6: Rating Favors by Asset Type: For MBS deals (red circles) and ABS deals (black crosses) we plot the unexplained *Deal Rating Implied-Spread* (given by the regression residuals $Log\ DRIS - \widehat{\beta}_C \mathbf{C}$ from Table 7, columns (1) and (3)) against the *Agency Specific Securitization Business* (in log scale) of the issuer as a "conflict of interest" proxy.

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). Yield Spread is winsorized at the 2.5% level. 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
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	312m	71m	867m	404	64.7bn
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
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	-	-	-	-
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
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

Table 2: Deal-Level Summary Statistics

Reported are summary statistics on the deal-level characteristics, the market term structure data at issuance and the imputed Deal Rating-Implied Spread (*DRIS*). PDS is short for Moody's database Performance Data Service, DCM is short for DCM Analytics and calcul. abbreviates calculated. *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 Appendix). Delinquency is winsorized at the 2.5%-level. For *Overcollateralization* and *Reserve Fund* the youngest available observation after deal closure is chosen (at most six months seasoning accepted). If *Deal Face Value* is missing for a deal, we use the sum of *Tranche Face Value* over the deal's tranches instead.

Variable	Description	Source	Obs	Mean	Median	Std. Dev.	Min	Max
A. Deal Level Rating Implied Spread (in %)								
DRIS(S&P)	Implied by S&P ratings	calcul.	5,655	0.14	0	0.37	0	2.61
DRIS(Moody's)	Implied by Moody's ratings	calcul.	5,196	0.12	0	0.29	0	2.61
DRIS(Fitch)	Implied by Fitch ratings	calcul.	3,561	0.08	0	0.25	0	2.61
DRIS	*DRIS* of all deal-CRA pairs	calcul.	14,412	0.12	0	0.32	0	2.61
Log DRIS	Ln(*DRIS* + 0.0024)	calcul.	14,412	−4.31	−6.02	2.11	−7.11	0.96
B. *AAA* Subordination Levels								
AAA subord. (S&P)	Deal fraction not AAA by S&P	calcul.	5,655	0.27	0.04	0.39	0	1
AAA subord. (Moody's)	Deal fraction not Aaa by Moody's	calcul.	5,196	0.21	0	0.35	0	1
AAA subord. (Fitch)	Deal fraction not AAA by Fitch	calcul.	3,561	0.13	0	0.25	0	1
AAA subord.	Deal fraction not AAA of all (d,a) pairs	calcul.	14,412	0.21	0	0.35	0	1
Log AAA subord.	Ln(*AAA Subord.* + 0.075)	calcul.	14,412	−3.17	−4.89	1.94	−4.89	0.01
C. Conflict of Interest Proxy								
ASSB	Business (USD) between CRA a and issuer of deal d in year of issuance	calcul.	4,026	$3.6bn$	$840m$	$12.6bn$	$1.2m$	$176bn$
Log ASSB	Natural log ASSB	calcul.	4,026	20.66	20.55	1.47	14.02	25.90
D. Deal Characteristics								
Deal Face Value	Face value in USD	DCM	7,118	$988m$	$553m$	$1.94bn$	63845	$69.5bn$
Log Deal Face Value	Natural log of deal face value	calcul.	7,118	20.01	20.13	1.30	11.06	24.96
Delinquency	Winsorized fraction (in %) of delinquent collateral 9mth after deal closure	PDS	764	1.27	0.38	2.18	0.00	9.51
Log Delinquency	Ln(*Del.* + 0.0045)	calcul.	764	−0.91	−0.96	1.62	−4.83	2.25
Deal Fraction with Guarantee	Ratio of guaranteed principal over deal face value	DCM	7,118	0.07	0.00	0.26	0.00	1.00
Overcollateral.	Ratio of collateral principal minus principal of securities over principal of securities	PDS	764	−0.02	0	0.36	−6.46	1
Reserve Fund	Reserves divided by principal of securities	PDS	764	0.03	0.01	0.04	0	0.39
Number of Tranches	No. of deal tranches	DCM	7,118	3.3	2	3.6	1	59
Unsecuritized Deal Part	Ratio of deal face value minus principal of securities over deal face value	calcul.	7,118	0.01	0	0.09	0.00	0.99
Single CRA	1 if all tranche ratings from same CRA	calcul.	7,118	0.09	-	-	-	-

Table 3: Estimating Rating-Implied Spreads

We regress tranche-level credit 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 1 month USD Libor rate at issuance as a proxy for the *Term Structure Level*; the difference between the 12 month and the 1 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	10625	10625	9314	9314

Table 4: AAA Subordination and Credit Risk

Reported are average deal characteristics, the number of observations and test results by Credit Rating Agency 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. The values of the variables *AAA Subordination*, *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	Value	$\|z\|$-stat	Obs.	Value	$\|z\|$-stat	Obs.	Value	$\|z\|$-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AAA Subordination									
All deals	5196	20.67		5655	27.09		3561	12.70	
Deals of top 10% clients	3799	12.62	32.34***	4123	20.44	26.36***	2673	7.35	29.26***
Deals of top 5% clients	3405	10.73	36.00***	3720	19.25	28.98***	2327	4.71	35.98***
Delinquency Rate									
All deals	657	1.23		470	1.56		374	1.50	
Deals of top 10% clients	459	1.37	2.19**	355	1.75	2.65***	230	1.88	3.85***
Deals of top 5% clients	334	1.34	0.10	273	2.05	3.60***	136	2.02	2.50**
Deal Fraction with Guarantee									
All deals	5196	8.50		5655	7.84		3561	8.07	
Deals of top 10% clients	3799	8.67	0.45	4123	7.98	0.24	2673	8.44	0.10
Deals of top 5% clients	3405	9.01	1.00	3720	8.21	0.19	2327	9.14	1.75*
Reserve Fund									
All deals	657	2.72		470	1.90		374	1.66	
Deals of top 10% clients	459	2.70	0.80	355	1.92	1.03	230	1.67	0.77
Deals of top 5% clients	334	2.69	2.29**	273	1.90	1.62	136	1.92	1.65
Overcollateralization									
All deals	657	−2.84		470	−3.84		374	−1.21	
Deals of top 10% clients	459	−0.76	0.43	355	−1.32	1.55	230	−0.51	2.22**
Deals of top 5% clients	334	−0.61	2.29**	273	−1.18	2.61***	136	−0.22	1.29
No. of Tranches									
All deals	5196	3.45		5655	3.39		3561	3.19	
Deals of top 10% clients	3799	3.02	26.63***	4123	3.04	24.13***	2673	2.81	23.86***
Deals of top 5% clients	3405	2.83	30.55***	3720	2.85	29.81***	2327	2.56	29.98***
Deal Face Value									
All deals	5196	1.08*bn*		5655	0.98*bn*		3561	1.16*bn*	
Deals of top 10% clients	3799	1.20*bn*	7.42***	4123	1.10*bn*	11.79***	2673	1.24*bn*	0.34
Deals of top 5% clients	3405	1.18*bn*	2.09**	3720	1.07*bn*	5.76***	2327	1.23*bn*	2.90***

Table 5: Conflict of Interest

We regress.the deal rating-implied spreads (calculated as natural logarithm $Log(DRIS + 0.0022)$) on conflict of interest proxies computed for all deal-CRA pairs as the natural logarithm of $ASSB(d, a)$. $ASSB(d, a)$ is the business between CRA a and the issuer of deal d in the issuance year of deal d. The controls are: *Log Deal Face Value* = natural logarithm of deal face value; *Log Delinquency* = natural logarithm of (*Delinquency* + 0.0045) 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. 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 DRIS			
	(1)	(2)	(3)	(4)
Log ASSB	-0.182^{**}	-0.255^{***}		-0.233^{***}
	(0.085)	(0.063)		(0.061)
Log Deal Face Value			-0.180^{**}	-0.099
			(0.082)	(0.077)
Controls:				
Log Delinquency	0.177^{**}	0.196^{**}	0.174^{**}	0.190^{**}
	(0.084)	(0.082)	(0.081)	(0.081)
Log Delinquency Squared	0.010	0.022	0.017	0.021
	(0.023)	(0.020)	(0.019)	(0.020)
Deal Fraction with Guarantee	-0.397	-0.184	-0.224	-0.234
	(0.262)	(0.162)	(0.176)	(0.165)
Overcollateralization	-0.265^{***}	-0.191^{***}	-0.158^{**}	-0.173^{**}
	(0.065)	(0.071)	(0.073)	(0.071)
Reserve Fund	-0.915	-2.378	-1.687	-2.278
	(2.180)	(1.876)	(1.890)	(1.855)
No. of Tranches	0.181^{***}	0.152^{***}	0.147^{***}	0.156^{***}
	(0.044)	(0.034)	(0.034)	(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	No	Yes	Yes	Yes
R^2	0.302	0.566	0.558	0.567
N	1501	1501	1501	1501

Table 6: Quantile Regressions

We run simultaneous quantile regressions for the natural logarithm $Log(DRIS + 0.0022)$ of the deal rating-implied spread. The independent variables are: *Log* $ASSB(d, a)$ = natural logarithm of $ASSB(d, a)$ which is the business between CRA a and the issuer of deal d in the issuance year of deal d; *Log Delinquency* = natural logarithm of (*Delinquency* + 0.0045) 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. Bootstrap standard errors (in parentheses) are computed on the basis of 400 repetitions. The symbols *,**, and *** represent significance levels of 10%, 5%, and 1% respectively. The between-quantile blocks in the variance-covariance matrix are used to test whether the *Log ASSB* coefficients at quantiles Q(10), Q(25), Q(50) and Q(75) are significantly different from the coefficient estimated at the Q(90). The F-statistic has one degree of freedom in the numerator and thus equlas the squared t-statistic which allows the computation of one-sided p-values for the null that the coefficient at the Q90 exceeds the coefficient at another quantile.

	Dependent Variable: Log DRIS					
	OLS	Quantile Regressions				
		Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
	(1)	(2)	(3)	(4)	(5)	(6)
Log ASSB	-0.182^{**}	-0.149^{***}	-0.149^{***}	-0.130^{***}	-0.159^{***}	-0.238^{***}
	(0.085)	(0.050)	(0.038)	(0.029)	(0.037)	(0.055)
Controls:						
Log Delinquency	0.177^{**}	0.252^{***}	0.191^{***}	0.193^{***}	0.170^{***}	0.030
	(0.084)	(0.050)	(0.046)	(0.040)	(0.050)	(0.090)
Log Delinquency Squared	0.010	0.027^{*}	0.010	0.020	0.007	−0.037
	(0.023)	(0.016)	(0.018)	(0.015)	(0.017)	(0.026)
Deal Fraction with Guarantee	−0.397	−0.371	−0.383	-0.366^{***}	-0.313^{*}	−0.238
	(0.262)	(0.418)	(0.296)	(0.131)	(0.162)	(0.283)
Overcollateralization	-0.265^{***}	-0.482^{*}	-0.523^{***}	-0.290^{*}	−0.096	−0.007
	(0.065)	(0.254)	(0.175)	(0.161)	(0.168)	(0.188)
Reserve Fund	−0.915	−1.355	−1.279	−0.333	2.988	4.107^{*}
	(2.180)	(3.498)	(3.230)	(1.547)	(2.191)	(2.113)
No. of Tranches	0.181^{***}	0.228^{***}	0.195^{***}	0.169^{***}	0.174^{***}	0.237^{***}
	(0.044)	(0.030)	(0.033)	(0.023)	(0.031)	(0.056)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Asset type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Collateral nationality fixed eff.	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2		0.34	0.26	0.22	0.20	0.23
N	1501	1501	1501	1501	1501	1501
Difference to Q(90) coefficient on *Log ASSB*:						
F-statistic (1, 1447)		1.65	2.30	4.45	3.43	
One-sided p-value		0.099	0.065	0.018	0.032	

Table 7: Conflict of Interest Across Asset Types

The deal rating-implied spread $DRIS(d,a)$ is computed for all deal-CRA pairs. Its natural logarithm $Log(DRIS + 0.0022)$ is regressed on the natural logarithm of $ASSB(d,a)$. $ASSB(d,a)$ is the business between CRA a and the issuer of deal d in the issuance year of deal d. Columns (1) and (2) consider the subsample of MBS and columns (3) and (4) the subsample of ABS. Columns (5) and (6) consider the full sample and include an interaction of *Log ASSB* with a dummy being one for ABS deals. Further dummies for commercial and residential MBS as well as for CLOs are included. The controls are: *Log Deal Face Value* = natural logarithm of deal face value; *Log Delinquency* = natural logarithm of (*Delinquency* + 0.0045) 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. 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 DRIS					
	MBS		ABS		ALL	
	(1)	(2)	(3)	(4)	(5)	(6)
Log ASSB	-0.275^{***}	-0.248^{***}	-0.389^{***}	-0.421^{***}	-0.275^{***}	-0.248^{***}
	(0.067)	(0.070)	(0.123)	(0.131)	(0.069)	(0.072)
ABS × *Log ASSB*					-0.135	-0.196
					(0.136)	(0.140)
Log Deal Face Value		-0.116		0.269		-0.116
		(0.095)		(0.338)		(0.097)
Controls:						
Log Delinquency	0.192^{*}	0.188^{*}	0.409^{**}	0.470^{**}	0.192^{*}	0.188^{*}
	(0.101)	(0.099)	(0.177)	(0.194)	(0.103)	(0.101)
Log Delinquency Squared	0.017	0.016	0.100	0.122^{*}	0.017	0.016
	(0.018)	(0.018)	(0.064)	(0.069)	(0.018)	(0.018)
Deal Fraction with Guarantee	-0.187	-0.230	-1.211	-0.879	-0.187	-0.230
	(0.190)	(0.193)	(0.749)	(0.883)	(0.194)	(0.196)
Overcollateralization	-0.192^{***}	-0.174^{***}	2.592^{*}	2.446	-0.192^{***}	-0.174^{**}
	(0.070)	(0.067)	(1.569)	(1.584)	(0.071)	(0.068)
Reserve Fund	-4.469	-4.311	2.416	1.651	-4.469	-4.311
	(2.725)	(2.671)	(2.948)	(2.634)	(2.775)	(2.721)
No. of Tranches	0.140^{***}	0.143^{***}	0.352^{***}	0.300^{***}	0.140^{***}	0.143^{***}
	(0.036)	(0.036)	(0.088)	(0.105)	(0.037)	(0.036)
Dummy: *residential MBS*					-1.057^{*}	-1.111^{*}
					(0.598)	(0.556)
Dummy: *commercial MBS*	1.057^{*}	1.111^{*}				
	(0.588)	(0.546)				
Dummy: *CLO*			0.398	0.274	0.284	0.150
			(0.342)	(0.342)	(0.326)	(0.326)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Collateral nationality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Issuer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Interactions: *ABS* × *Controls*	No	No	No	No	Yes	Yes
R^2	0.568	0.570	0.781	0.784	0.633	0.635
N	1117	1117	384	384	1501	1501

Table 8: Credit Cycles, Ratings Shopping and Agency Fixed Effects

The deal rating-implied spread $DRIS(d,a)$ is computed for all deal-CRA pairs. Its natural logarithm $Log(DRIS+0.0022)$ is regressed on the natural logarithm of $ASSB(d,a)$. $ASSB(d,a)$ is the business between CRA a and the issuer of deal d in the issuance year of deal d. Column (1) includes two interaction terms between credit boom and crisis dummies and *Log ASSB*. Column (2) includes a dummy which is one if all ratings of a deal were produced by one single CRA. The specification further includes two interactions of the dummy *Single CRA* with a credit boom and a crisis dummy. Specification (3) includes CRA fixed effects and column (4) additionally includes interactions between CRA dummies and *Log ASSB*. The controls are: *Log Deal Face Value* = natural logarithm of deal face value; *Log Delinquency* = natural logarithm of (*Delinquency* + 0.0045) 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. 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 DRIS			
	(1)	(2)	(3)	(4)
Log ASSB	-0.093	-0.251^{***}	-0.237^{***}	-0.202^{***}
	(0.083)	(0.061)	(0.061)	(0.061)
Log Deal Face Value	-0.122	-0.117	-0.099	-0.096
	(0.077)	(0.078)	(0.077)	(0.077)
Issued 2004-06 × *Log ASSB*	-0.343^{***}			
	(0.114)			
Issued 2007-08 × *Log ASSB*	-0.131			
	(0.097)			
Dummy: *Single CRA*		0.807^{**}		
		(0.374)		
Issued 2004-06 × *Single CRA*		-1.389^{**}		
		(0.582)		
Issued 2007-08 × *Single CRA*		-0.291		
		(0.418)		
Dummy: *S&P*			-0.057	0.753
			(0.051)	(0.695)
Dummy: *Fitch*			-0.044	2.124^{***}
			(0.043)	(0.749)
S&P × *Log ASSB*				-0.037
				(0.031)
Fitch × *Log ASSB*				-0.098^{***}
				(0.033)
Controls:				
Log Delinquency	0.186^{**}	0.153^{*}	0.190^{**}	0.188^{**}
	(0.076)	(0.085)	(0.081)	(0.081)
Log Delinquency Squared	0.018	0.014	0.020	0.020
	(0.019)	(0.020)	(0.020)	(0.020)
Deal Fraction with Guarantee	-0.238	-0.173	-0.234	-0.241
	(0.162)	(0.171)	(0.167)	(0.166)
Overcollateralization	-0.110	-0.167^{***}	-0.173^{**}	-0.174^{**}
	(0.078)	(0.067)	(0.071)	(0.071)
Reserve Fund	-2.317	-2.027	-2.302	-2.255
	(1.906)	(1.863)	(1.858)	(1.858)
No. of Tranches	0.164^{***}	0.159^{***}	0.156^{***}	0.157^{***}
	(0.034)	(0.031)	(0.033)	(0.034)
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	0.576	0.577	0.567	0.569
N	1501	1501	1501	1501

Table 9: Robustness

We define alternative dependent variables as a robustness exercise and repeat the base line regression of Section 5.1.1. The dependent variable in the first four columns is the natural logarithm of the deal rating-implied spread $DRIS$. However, in the first two columns the computation of $DRIS$ charges the average RIS of the tranches in our sample to the unsecuritized part of a deal. By contrast, the unsecuritized deal part is weighted with the highest possible RIS implied by *Junk* in columns (3) and (4). The dependent variable in columns (5) and (6) is $DRIS$ corrected for any premium that investors could require for the risk of rating favors. The corrected $DRIS$ is estimated on the basis of Equation 6 which includes a control for conflicts of interest. The dependent variable in the last two columns is the natural logarithm Log(*AAA Subordination* + 0.0075) of the deal part that is not rated *AAA*. The independent variables are: *Log* $ASSB(d, a)$ = natural logarithm of $ASSB(d, a)$ which is the business between CRA a and the issuer of deal d in the issuance year of deal d; *Log Deal Face Value* = natural logarithm of deal face value; *Log Delinquency* = natural logarithm of (*Delinquency* + 0.0045) 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. 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 DRIS with unsecuritized deal part weighted:				Corrected Log DRIS:		Log AAA-subordination	
	Avg. RIS		$RIS(Junk)$		(no rating favor premium)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log ASSB	−0.197***	−0.151**	−0.261***	−0.240***	−0.239***	−0.225***	−0.174***	−0.127**
	(0.063)	(0.066)	(0.064)	(0.062)	(0.063)	(0.066)	(0.055)	(0.056)
Log Deal Face Value		−0.208***		−0.092		−0.064		−0.210***
		(0.085)		(0.079)		(0.088)		(0.071)
Controls:								
Log Delinquency	0.187**	0.174**	0.200**	0.194**	0.201*	0.197*	0.143*	0.130*
	(0.084)	(0.079)	(0.083)	(0.082)	(0.104)	(0.103)	(0.077)	(0.072)
Log Delinquency Squared	0.028	0.024	0.023	0.021	0.026	0.025	0.026*	0.022
	(0.019)	(0.018)	(0.020)	(0.020)	(0.026)	(0.026)	(0.016)	(0.016)
Deal Fraction with Guarantee	−0.141	−0.247	−0.186	−0.233	−0.188	−0.221	−0.209	−0.315**
	(0.179)	(0.187)	(0.164)	(0.167)	(0.148)	(0.138)	(0.150)	(0.131)
Overcollateralization	−0.255***	−0.218***	−0.188**	−0.172**	−0.234***	−0.223***	−0.179***	−0.142***
	(0.066)	(0.067)	(0.073)	(0.073)	(0.064)	(0.062)	(0.045)	(0.046)
Reserve Fund	−2.051	−1.841	−2.451	−2.358	−1.240	−1.175	−1.706	−1.495
	(1.860)	(1.848)	(1.914)	(1.894)	(2.522)	(2.517)	(1.778)	(1.741)
No. of Tranches	0.145***	0.154***	0.155***	0.159***	0.106***	0.110***	0.108***	0.117***
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.027)	(0.024)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral nationality fixed eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.539	0.544	0.561	0.562	0.525	0.530	0.571	0.578
N	1501	1501	1501	1501	1501	1501	1501	1501

Appendix

Dataset and Variable Construction

Our analysis is based on a dataset combining tranche-level and deal-level information from several sources. We merge and analyze the data in several steps:

Step 1: Merge DCM Analytics, Bloomberg and Thomson Reuters Datastream

DCM Analytics is provided by dealogic. We extract all securities

- that were issued in Europe or North America,
- that were issued between January 1999 and December 2011,
- that have an ISIN identifier,
- whose issuer is known in DCM Analytics,
- that are ABS or MBS.

The sample obtained comprises 22,359 different ISIN, which are part of 7,118 different deals. We retrieve launch ratings, coupons, tranche and deal face values, names of issuers, issuer parents and guarantors, issuance dates as well as information on collateral nationality and asset types. We use ISINs to merge DCM Analytics with data about issuance prices, currencies and weighted average lives at issuance from Bloomberg. We use the issuance dates of securities to merge the sample with data from Thomson Reuters Datastream from which we retrieve the Libor or Euribor rate at the issuance date of a security.

Step 2: Encode Credit Ratings

The launch ratings of Moody's are mapped into the rating scales of S&P or Fitch ratings (*AAA* for *Aaa* and so on down to *BBB-* for *Baa3*). As relatively few securities have a rating below *BB-*, ratings below investment-grade are pooled in one group labeled *Junk*. This approach gives 11 rating values from *AAA* down to *Junk*. We introduce three additional rating values for unrated securities (see Section 4.1).[30] If a tranche is rated by more than one CRA, we aggregate its different ratings into one composite rating for the purpose of estimating rating-implied spreads in Section 4.1. If the security has two ratings, the more conservative rating is used. If the security has three ratings, the median rating is chosen.[31]

Step 3: Data Filters

We undertake some data cleaning for extreme observations. We winsorize coupon spreads over Euribor/Libor at the 2.5% percentile. Furthermore, we set the spread value to *missing* if

[30] We concentrate on long-term ratings. If a security only has a short-term rating, we consider it to be unrated.

[31] This procedure is consistent with the "most prevalent institutional rule used for classifying rated bonds" (Bongaerts *et al.* (2012, p.114)) and is used under the Standard Approach of Basel II (BCBS (2006), p.24).

it equals zero for a security that was issued at par but carries a junk rating. We also correct the reported deal face value if it is smaller than the combined face value of all deal tranches together. Finally, we replace the deal face value by the combined face value of all deal tranches if the deal face value itself is misisng.

Step 4: Pricing Model and Estimation of Rating-Implied Spreads (*RIS*)

With the data from DCM Analytics, Bloomberg and Datastream we estimate the pricing model for rating-implied spreads of Section 4.1. The relevant subsample for the full specification comprises 9,045 floaters that are issued at par, have the Euribor or Libor as base rate and data on all variables shown in Table 3. The rating dummies equal zero or 1 depending on the composite rating defined under Step 2. Standard errors are clustered at deal level. For all 22,359 securities in our sample (constructed under Step 1) we use the estimated coefficients on the rating dummies (see Table 3) to compute rating-implied spreads RIS.[32] For example, a tranche rated $Baa2$ by Moody's, $BBB-$ by S&P and $BB+$ by Fitch has the following RIS: *RIS(Baa2 by Moody's)*$= 78bp$, *RIS(BBB- by S&P)*$= 88.5bp$ and *RIS(Junk by Fitch)*$= 260.9bp$.

Step 5: Portfolio Model and Aggregation of Spreads to Deal-Level

For each deal-CRA pair we compute the deal rating-implied spread $DRIS(d, a)$ as defined in Equation 2. If a CRA has not rated a single tranche of a deal, no $DRIS(d, a)$ is computed for this deal-CRA pair. If the combined face value of a deal's different tranches is smaller than the deal face value reported in DCM Analytics, we interpret the difference as a junior tranche which has not been securitized by the issuer. The average size in % of the deal face value is 1.5%. We charge this unsecuritized junior tranche the RIS implied by the dummy for *Unrated Junior*. Robustness checks in Section 6.2 show that the treatment of unsecuritized deal parts is uncritical for our results.

Step 6: Filter Data from Performance Data Services

Performance Data Services provided by Moody's contain information on collateral pools, deals and individual deal tranches. We apply some data cleaning to correct obvious data errors and ambiguities.

- We drop deals whose tranche issuance dates deviate by more than 31 days from the deal closure date.
- Some deals are backed by several collateral pools throughout their existence. As the data do not tell which collateral pool was the relevant one at the date when the deal received its launch ratings, we must drop all deals backed by several collateral pools.
- Some collateral pools back several deals. We only keep the oldest deal that was first issued against a collateral pool, assuming that CRAs do not expect the issuer to use the same collateral pool to back other deals in the future.

[32] Unrated securities receive the RIS implied by *Unrated Junior*, *Unrated Mezzanine/Junior* or *Unrated Senior/Mezzanine/Junior*.

Step 7: Compute Delinquency Rates and Credit Enhancement

For each deal we retrieve the 90-plus delinquency rate nine months after deal closure. For some deals this observation does not exist. In those cases we choose the delinquency observation $Del(s)$ whose seasoning s is closest to nine months and make a linear adjustment:

$$\begin{aligned} Del(s) &= \tfrac{Del(270)}{270-90} \cdot (s-90) \\ \Leftrightarrow \quad Del(270) &= \tfrac{Del(s)}{s-90} \cdot (270-90) \end{aligned} \tag{A1}$$

We assume that the fraction of collateral that is at least 90 days delinquent increases proportionally at rate $\frac{Del(s=270)}{270-90}$ over time. Starting 90 days after deal closure the 90-plus delinquency rate of a deal with s days seasoning has increased to $\frac{Del(s=270)}{270-90} \cdot (s-90)$. Under this assumption we make the adjustment in (A1). To limit potential biases, we only apply this linear approximation to observations whose seasoning is between six and 12 months. Deals without a delinquency observation in that seasoning window are dropped. Furthermore, we retrieve information on overcollateralization and liquidity reserves (reserve funds) from Performance Data Services.[33] Both variables are standardized by the outstanding principal value of the securitized tranches. Optimally, both variables are measured at the issuance date when the launch ratings are attributed. Therefore, we choose the observation with the smallest seasoning. If this observations lies more than six months after deal closure, we drop the deal.

Step 8: Merge *DRIS* and Control Variables

We use ISINs to merge the variables computed with data from DCM analytics with the delinquency and credit enhancement information from Performance Data Services. The cut-set comprises 764 European deals. In this sample we winsorize the adjusted delinquency rates at the 2.5% percentile.

Step 9: Regression Analyses

After dropping all observations that have not been rated by any CRA, 726 deals remain. The corresponding 1,501 deal-CRA pairs are the basis for the regression analyses in Sections 5 and 6. Figure 7 provides quantile plots for our base-line regression. The distribution of the regression residuals for specifications (2) and (4) in Table 4 appear to be sufficiently normal.

[33] If the value of overcollateralization or liquidity reserve is missing, we conclude that this deal had no liquidity or collateral reserves. The control *Deal Fraction with Guarantee* is computed with data from DCM Analytics.

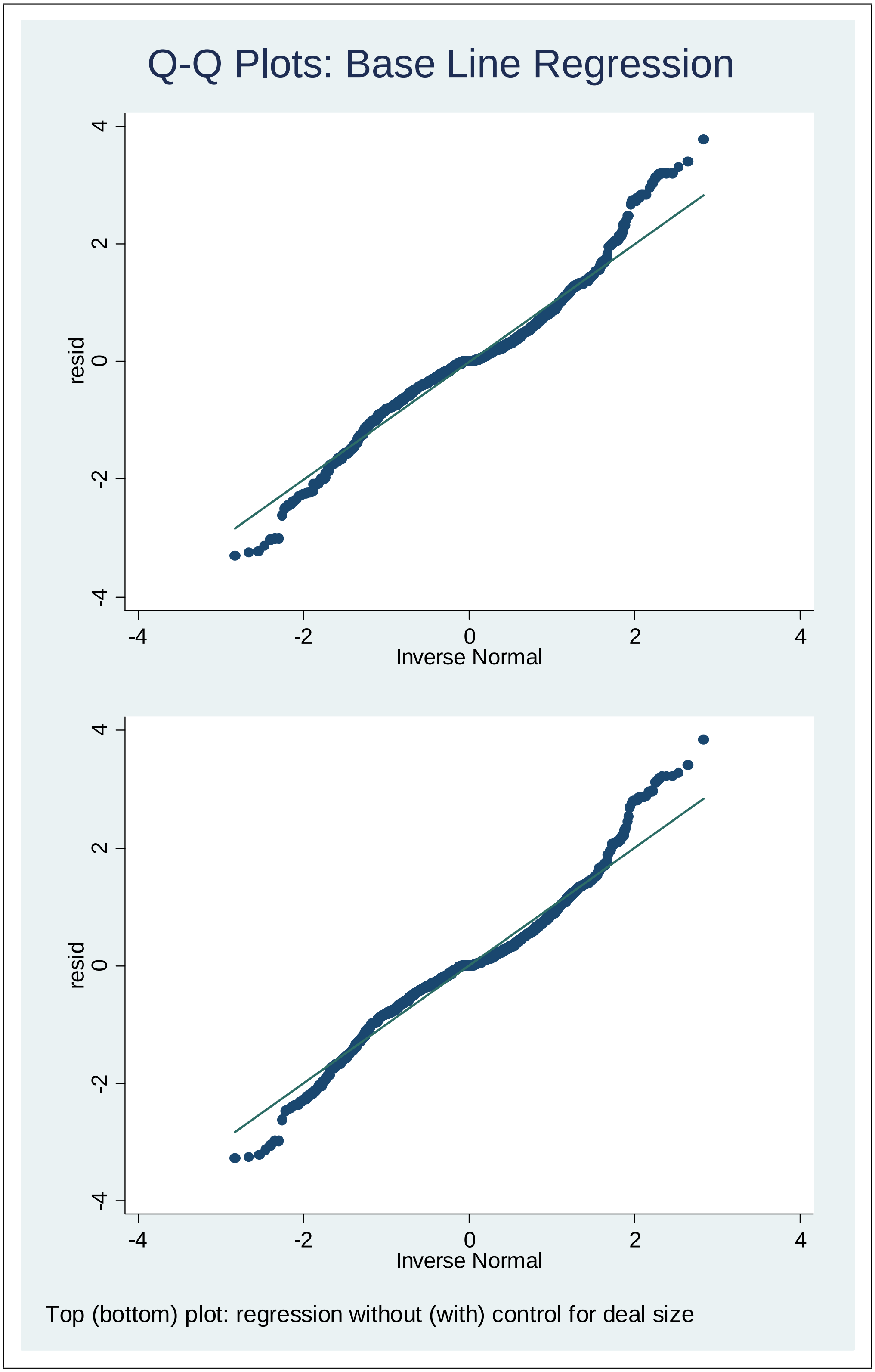

Figure 7: Q-Q plots for Specifications (2) and (4) of Table 5.