Empirical Analysis of Credit Ratings Inflation as a Game of Incomplete Information *

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Abstract

I study rating agency behavior in the market for commercial mortgage-backed securities (CMBS). CMBS issuers hire rating agencies in a manner akin to an auction, where an agency's "bid" comprises a stated standard for a security to get a AAA rating. Equilibrium ratings give a biased representation of agencies' true beliefs due to a selection effect (only the most favorable ratings are published) and because the agencies trade off between incentives to rate truthfully and incentives to bid strategically in order to increase the probability of being hired to rate the deal. I identify the agencies' true beliefs by modeling bidding behavior and exploiting a novel source of bidder-specific data. I find that the true beliefs are an important predictor of the ex post realized performance of the securities, even after controlling for the equilibrium ratings. I also investigate the extent of ratings distortion under various counterfactual regimes motivated by proposed policy reforms.

*I thank Morningstar for supplying the data. Views expressed herein are mine and do not reflect the views of the Federal Reserve Board of Governors or Staff.

Instructions to Sandra Parker, a freelance writer hired by a review factory to write reviews for online retailers for $10 each: "We were not asked to provide a five-star review, but would be asked to turn down an assignment if we could not give one."[1]

1. INTRODUCTION

Product reviewers that are compensated by parties with a financial interest in the reviews have an incentive to distort their true opinions. Examples of the phenomenon include real estate appraisers that are hired by mortgage lenders and online reviewers that are paid to do reviews by business owners.[2] In this paper, I quantify the extent to which strategic considerations distort credit ratings for financial securities. Indeed, the inflation of ratings for innovations such as "collateralized debt obligations (CDOs)" and subprime mortgage-backed securities has widely been blamed for contributing to the recent financial crisis.

In principle, credit rating agencies may serve either of two functions. First, they may play a role as quality certifiers. For example, institutions such as pension funds are restricted to investing in "investment-grade" or other relatively safe instruments, and a rating is a tool for monitoring compliance. Similarly, higher ratings can also reduce the regulatory capital required for securities held by a regulated bank. Second, if assessing the quality of a security is costly to investors, rating agencies may play a role as producers and disseminators of information. By reducing asymmetric information between security issuers and investors, the agencies may increase market efficiency.

A key feature of the rating agencies' business model is that the three largest competitors are compensated by the bond issuers and not by investors. This arrangement creates perverse incentives, both because the agencies have heterogeneous beliefs and issuers can "rating shop" by selectively picking the most favorable ratings for publication, and because the agencies have an incentive to inflate their ratings in order to increase the probability of being selected to rate the deal. Distorted ratings are problematic whether the rating agencies' role is to certify quality or to reduce asymmetric information. In the former case, inflated certifications could allow market participants such as banks and pension funds to take on greater risks than desired by regulators; in the latter case, if investors are naïve about how ratings are determined, they may underestimate the

[1] New York Times, "In a Race to Out-Rave, 5-Star Web Reviews Go for $5," by David Streitfeld, August 19, 2011.

[2] "Yelp clamps down on paid reviews with new 'consumer alert,"' Article in CNET, October 18, 2012 (available online).

true risk of their investments. Furthermore, even if investors are sophisticated, ratings distortion may create market inefficiencies if there is not full revelation of the agencies' private information.

I study rating agency behavior using data on commercial mortgage-backed security (CMBS) deals issued between 2000 and 2010. Each CMBS deal is backed by a pool of collateral comprising mortgages on commercial properties (office buildings, apartments, retail space, etc.). Multiple securities are issued from each deal. These securities are bonds for which the bondholder has a claim on the future principal and interest payments from the underlying mortgages. The securities are "tranched" in order of seniority. Senior bondholders are partly shielded from the risk of mortgage borrower default, because the holders of subordinate securities take the first loss: the greater the subordination for a particular bond, the more protected it is from credit losses. A rating, such as "AAA" or "BB," is an opinion about the credit risk of the bond, taking into account the amount of subordination for the bond and the characteristics of the underlying collateral pool.

I model the behavior of rating agencies and CMBS issuers using an auction framework. When structuring a deal, the issuer solicits a "bid" from each agency indicating how the agency would rate the deal. The main component of the bid is an indication of the subordination that the agency would require for the AAA tranche, which the agency chooses as a function of its true belief about the quality of the pool. After receiving the bids, the issuer chooses a subset of the agencies and pays them to publish their ratings, and structures the deal in conformance with the strictest subordination requirements among those given by the selected agencies. Equilibrium ratings are distorted for two reasons. First, there is selection bias because the issuer would like to maximize the amount of the security that it can market as AAA-rated, and thus chooses the agencies requiring the least subordination. Second, agencies bid strategically, trading off between the probability of winning and the disutility from bidding dishonestly by requiring less subordination than they truly believe is necessary for a AAA rating.

As is common in many empirical auction settings, it is not possible to observe the entire set of bids, but only the "pivotal" bid that determines the equilibrium deal structure.[3] In general, such a data limitation would present a challenge for identification under all but the most restrictive, independent private values, assumption.[4] Fortunately,

[3]As I will explain, the pivotal bid is the same as the winning bid when each auction can have only a single winner, but is defined somewhat differently when there are multiple winners.

[4]See Athey and Haile, (2002) for an extensive discussion of identification issues in auction models.

I observe bidder-specific covariates in the form of hand-collected data from "pre-sale" reports that each agency released to investors just before each deal was issued. The pre-sale report provides the agency's assessment of specific loans in each deal and is thus indicative of the agency's private beliefs at the time of bidding.[5] This information allows us to identify the model under a more general specification of bidders' values. The degree of ratings distortion due to strategic bidding is implied by comparing the pivotal bidders' true beliefs against the observed subordination structure of the deal. On average, the true beliefs of the winning bidders imply an expected loss on the "AAA" tranche that corresponds roughly to a "Baa3" rating.

In addition to the novel information from the pre-sale reports, another strength of the data is that I observe the ex post performance of each deal, as reflected in realized losses on the mortgage pool. Controlling for equilibrium AAA subordination, for an increase in the pivotal bidder's belief equal to one standard deviation (across deals) in the amount of distortion, there is a 4-percentage point decrease in the ex post loss on the pool. Because the auction model does not impose a particular relationship between the agencies' beliefs and ex post performance, this finding provides a form of model validation. Conceptually, bidders' beliefs may have informational content after controlling for equilibrium AAA subordination because the latter is an order statistic of the bids, and does not completely reveal the agencies' full set of private information.

The final part of the paper simulates outcomes under various counterfactual scenarios motivated by policy reforms that have been proposed in the crisis aftermath. The first counterfactual explores the consequences of having fewer rating agencies, which weakens the agencies' incentive to bid strategically. The second scenario examines the impact of increasing the agencies' preference for truth-telling, which simulates the effect of heightened regulatory scrutiny. The final scenario supposes that the agencies had to share the contents of their pre-sale reports with each other before bidding, which approximates the effects of proposed regulations requiring agencies to divulge their rating model inputs to each other.

My paper is related to a number of theoretical papers on credit rating, none of which has an empirical counterpart or uses an auction framework to model the agents' interactions. Skreta and Veldkamp (2009) show that greater deal complexity intensifies issuers' incentive to rating shop. They focus on the issuers' choice over alternative ratings, but

[5] As I will argue in the body of the paper, the timing of when the pre-sale reports are released—after the auction is already over—makes it unlikely that they are written strategically.

treat rating agency behavior as nonstrategic. A complementary paper by Mathis, McAndrews, and Rochet (2008) assume that there is a monopoly rating agency (ruling out rating shopping) and model the monopolist's dynamic reputational incentives. They show that if investors believe the rating agency is intrinsically honest with some probability, a monopoly rating agency that behaves strategically can build up a stock of reputation by being truthful for some time before "cashing out." Bolton, Freixas, and Shapiro (2009) assume that rating agencies produce a binary "good" or "bad" rating. They show that a duopoly structure is generally less efficient than a monopoly rating agency due to rating shopping, and that rating agencies inflate ratings more as the proportion of naïve investors increases.

The existence of distortions in credit ratings is well-documented in the descriptive empirical literature. Cohen and Manuszak (2013) show that the percentage of a CMBS deal that is rated AAA is correlated with instruments proxying for the intensity of competition among rating agencies for that deal. Griffin and Tang (2011, 2012) find that the actual subordination levels for AAA-rated CDO securities were systematically lower than the levels required by the rating agencies' internal CDO-rating models (the latter of which the authors directly observe), and that the actual ratings are also contradicted by the agencies' own "surveillance" teams that monitor deals after they are issued. Becker and Milbourn (2011) find that increased competition from Fitch beginning in 1989 caused the incumbents, Standard and Poor's (S&P) and Moody's, to increase their ratings on corporate bonds, and reduced the informativeness of the ratings for observed bond prices and realized default outcomes.[6]

This paper contributes to the broader literature on the role of information intermediaries and quality certifiers (e.g., Lizzeri, 1999; Faure-Grimaud, A., E. Peyrache, and L. Quesada, 2009). Relative to the existing empirical work, my first key contribution is to quantify the *degree* to which strategic behavior distorts equilibrium ratings, while explicitly modeling the process by which rating agencies are selected. I can then quantify the importance of the distortion for explaining ex post outcomes. A second key contribution is that, because I identify the structural parameters of the model, I am able to examine the impact of counterfactual policy proposals, which previous research has not been able to do.

The focus of this paper is on strategic behavior by the rating agencies, whereas

[6]Moody's and S&P were a virtual duopoly over the market for rating corporate bonds until the entry of Fitch. By contrast, the market for rating structured finance instruments such as CMBS has been dominated by all three firms from the very start.

the CMBS issuer as auctioneer follows a relatively simple decision rule. Conceptually, this decision rule should be optimal given the behavior of investors—which I do not explicitly model—because the issuer's profits ultimately depend on the proceeds from selling the bonds. I address investor behavior in separate work in progress. However, the assumed decision rule is robust to various alternative behavioral assumptions about the investors—e.g., how investors form beliefs and whether investors' demand for ratings is driven by their informational content or by their certification value.

The rest of this paper proceeds as follows. Section 2 provides additional background on the industry, and Section 3 discusses data and descriptive findings. Section 4 presents the model and estimation procedure, and Section 5 discusses the estimation results. Section 6 relates the implied rating distortions to the ex post performance of deals. This section also relates the implied distortions to bond pricing data. Section 7 discusses counterfactuals, and Section 8 concludes.

2. THE CMBS INDUSTRY

Between the 1990s and the recent financial crisis, CMBS grew into a major source of financing for commercial mortgages, and by 2007 accounted for 53 percent ($180B) of all new loan originations.[7] Each CMBS deal is put together by a *lead underwriter*. I use the term "issuer" synonymously with "lead underwriter."[8] During the sample period, about twenty investment and commercial banks (e.g., J. P. Morgan Chase, Bank of America, Credit Suisse, and Goldman Sachs) dominated the CMBS issuance market.

To put together a deal, the issuer first assembles a set of loans to place in the collateral pool.[9] The issuer structures the future cashflows from principal and interest payments on the pool into prioritized claims ("tranches"), with each tranche being a marketable security. Within a deal, investors pay a premium for more senior securities, whose principal is shielded from losses by the subordinated, junior tranches. That is, investors in given tranche receive principal payments before tranches junior to it, which absorb losses due to loan defaults up to the point at which the junior tranches are wiped out.[10]

[7]Federal Reserve December 2011 Flow of Funds Tables F.219, and F.220. Figure includes $42B in loans backed by government-sponsored enterprises and agencies, which are not included in our data.

[8]Industry jargon sometimes differs from my usage, using "issuer" to refer to any originator with loans in the deal, not just the lead underwriter. Some deals have two or three co-lead underwriters, but the co-leads behave as a single agent.

[9]The loans may either be originated in-house by the issuer or may be purchased from unaffiliated originators—either other CMBS issuers or loan originators that do not themselves issue CMBS.

[10]Unlike the case for senior bonds of residential MBS deals, CMBS securities are largely shielded

Some of the premium for more senior securities also stems from regulatory incentives, such as lower bank capital requirements for holding higher-rated securities. It is an industry norm for the deals to be structured in such a way that the most senior tranches are always rated AAA. Because investors pay a premium for higher ratings, the issuers would like to maximize the proportion of higher-rated tranches in general, and of the AAA tranche in particular, which on average comprises about 80 percent of the pool principal. Of course, increasing the AAA tranche's proportion reduces the amount of subordination protecting the AAA bondholders, making it riskier and thus less worthy of a AAA rating.[11]

The rating agencies play a role during the deal structuring process. Typically, an issuer approaches several rating agencies for a "shadow" rating—that is, an indication of how it would rate the bonds, given various alternative possible deal structures. A key component the shadow rating is an indication of how much subordination the most senior tranche would have to have in order for it to receive a AAA rating, which we can think of as the agency's bid.[12] This formulation is somewhat of an abstraction, because in practice the shadow rating is multidimensional and also includes subordination requirements for the junior bonds. However, required AAA subordination captures the most important component of the shadow rating, and should in principle be highly correlated with the subordination that the agency requires for the subordinate bonds to receive their respective ratings.[13]

I assume an exogenous bidder set comprising the firms S&P, Moody's, and Fitch. The agencies do not typically charge the issuer a substantial fee for producing a preliminary

from prepayment risk. (Prepayment results in the bonds having shorter duration, which is undesirable if the coupon on the bond is higher than prevailing market rates.) Prepayment risk is not a significant factor in CMBS, where prepayment typically takes place by means of defeasance: the borrower is required to substitute other income-producing collateral (typically U.S. Treasuries) to produce the same stream of income as that which would have been generated by the prepaid loan.

[11]In practice, there may be additional complications to this basic schema. For example, "interest-only" (IO) tranches may be carved out of interest payments that would otherwise go to other tranches. Deal complexity increased over the 2000s, as investors demanded ever more specific contingent claims (Furfine, 2010).

[12]In practice, the shadow ratings may be determined to some extent through a process of negotiation between the issuer and each agency. However, conversations with rating industry practitioners indicate that the rating agencies never learn about their competitors' shadow ratings.

[13]The amount of subordination that the rating agency would require for a particular rating is highly correlated across tranches, because the ratings on all tranches are determined by the agency's perception of the overall pool quality.

assessment (if they charge at all), but rather, mainly profit from charging a fee for publishing the final rating.[14] Thus it makes sense that, according to conversations with market participants, all three major competitors are typically approached for a shadow rating.[15]

After obtaining the bids, the issuer chooses a subset of the bidders as the "winners" and pays them to publish their ratings. The issuer can choose one, two, or all three bidders to be winners, and must structure the deal in a manner that satisfies the subordination requirements implied by the shadow rating of every chosen bidder. In particular, the AAA subordination must be set to the maximum amount required by all chosen bidders.

Most typically in the data, the number of winners conforms to an industry norm requiring two ratings, which is based on the common perception that a second opinion provides corroboration, and satisfies the internal investment guidelines for certain institutional investors such as pension funds and cities.[16] Nevertheless, 7 percent and 10 percent of the deals have one or three winners, respectively. In my base model specification, I assume that the number of winners is exogenously determined. However, it is also possible to endogenize the number of winners by recognizing the following tradeoff. On the one hand, in expectation, choosing fewer winners increases the AAA tranche's proportion, which is the n'th order statistic of the bids when there are n winners. On the other hand, sophisticated investors would recognize that the published ratings are the least conservative ones, and may place a discount on deals with fewer published ratings

3. DATA

My two main data sources are the CMBS data vendor Morningstar and the presale reports that the agencies distributed to potential investors immediately before the

[14] "Typically, the rating agency is paid only if the credit rating is issued, though sometimes it receives a breakup fee for the analytic work undertaken even if the credit rating is not issued." SEC (2008), p. 9.

[15] The issuer may also approach one or more of the fringe competitors. DBRS, Morningstar (formerly Realpoint), and Kroll are newer market entrants with a significantly smaller market share. For purposes of the analysis, I ignore their presence.

[16] For example, see Basel Committee (2012): "Requiring at least two ratings and using the lower of the two (or the second best in the case of more than two available ratings) helps to reduce over-reliance on a single rating agency's assessment of risk."

securities were issued.[17] I have data for observations at the level of the individual loans, for deals, and for the tranched securities. The various types of data are detailed below.

For each of the 60,748 loans in the sample, I observe the standard characteristics observed by market participants as of the time of the loans' origination. The loans' characteristics determine their default risk either causally—by affecting the borrowers' incentives—or due to borrower self-selection into certain types of loans. The two most important characteristics are the debt-service coverage ratio (DSCR) and the loan-to-value (LTV) ratio. The DSCR is the ratio of the borrower's monthly rental and other income to mortgage payments, and measures the borrower's ability to make monthly payments on the mortgage. The LTV is the ratio of the loan amount to the assessed property value, and measures the borrower's equity in the property. Thus, a lower DSCR or a higher LTV each corresponds to greater risk of default. Other observed characteristics include the mortgage type (rate type, amortization schedule, and maturity)—with virtually all loans having fixed (versus floating) interest rates, and most having a 30-year amortization schedule with a 10-year maturity (implying a balloon payment after 10 years). I also observe the origination year (ranging from 1999 to 2010), the original principal amount, and the coupon spread (i.e., the interest rate on the loan expressed as a premium over a benchmark rate).[18] I also observe the type of institution that originated each loan, which is correlated with systematic differences in borrower quality (Black et al., 2011).[19]

At the deal level, I observe characteristics such as the identity of the issuer, the date of issuance, the identities of the mortgages in the collateral pool, and the identities of the winning bidders. I also observe the tranche structure of the securities and the initial rating of each security by the rating agencies, allowing me to construct the total principal balance of all tranches rated AAA.[20]

[17]As noted previously, Morningstar is a new-entrant rating agency. Morningstar follows a subscription-based rather than issuer-paid business model. This fact is tangential to my analysis, because I use the data from the subscription service but do not treat Morningstar as an active player in the model, given its limited presence in the market during much of the sample period.

[18]I set the benchmark rate to the U.S. Treasury yield for the same maturity as the loan, as of the month of origination. The coupon spread depends largely on the lender's perception of the borrower's credit quality, but also on the lender's market power and overall portfolio strategy, time-varying risk premia, and other factors affecting the loan's cost.

[19]The categories are commercial banks, investment banks, insurance companies, independent finance companies, foreign conduits, and domestic conduits.

[20]Ratings data are missing for some rated tranches, so summing the balances for tranches with

I observe ex post performance at both the loan level and at the deal level. At the loan level, I observe the payment history of each mortgage borrower through the censoring date of June 2011, from which we can infer whether the loan defaults and, if so, at what point in time. At the deal level, I observe the total amount of written-down pool principal and the total shortfall in interest payments from the mortgage borrowers as of the censoring date.

A rating agency's pre-sale report for a given deal is a document describing the underlying loans and the tranche structure of the deal. The critical piece of information in it that I use is the agency's private assessment (based on its reviewing documents and physically inspecting properties) of the DSCR and LTV for the largest loans and for the overall pool, expressed as a weighted average by loan principal. These "reunderwritten" DSCR and LTV values typically differ from the DSCR and LTV underwritten by the loan originators.[21]

3.1. *Descriptive Facts*

Table 1 shows summary statistics at the deal level. The reported statistics include weighted-average loan characteristics, weighted by loan size; concentration indices (Herfindahl-Hirschmann) for the distribution of property types, regions, and MSAs in the pool; and the HHI for individual loans' share of the pool principal. The concentration indices proxy for pool diversification.

S&P, Moody's, and Fitch published ratings for 70.1, 70.5, and 58.1 percent of the deals, respectively, and produced pre-sale reports for respectively 92.8, 72.2, and 95.5 percent of the deals for which they published ratings. The average AAA subordination is 17.2 percent of the pool principle.[22]

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an observed AAA rating understates the true AAA balance. To mitigate this problem, I assume that tranches with the maximum reported level of subordination in a deal are always AAA, and take the AAA principal to be the greater of the balance of these tranches and the balance of all tranches with an observed AAA rating.

[21] S&P reports an "actual" DSCR—the ratio of S&P's forecast future cashflows, which have "an inherent 'BBB' stress" built in via various adjustments, to scheduled debt service (S&P, 2009). Fitch reports a "stressed" DSCR, which is the average of a DSCR computed using the scheduled debt service and an alternative DSCR accounting for the need to refinance the balloon payment at maturity (detailed in Fitch, 2008). Moody's reports both an "actual" and a "stressed" DSCR (detailed in Moody's, 2000). For my purposes, I use the "actual" DSCR for S&P and the "stressed" DSCR for Moody's and Fitch. All three agencies render an opinion on the "actual" LTV.

[22] Early in the history of CMBS (i.e., the late 1990s and early 2000s), deals typically had only a

The weighted average reunderwritten DSCR from the pre-sale reports is systematically lower than the weighted average original DSCR as underwritten by the originators, indicating that the agencies are generally more pessimistic than the originators about future income streams on the collateral properties underlying the loans.[23] Similarly, the reunderwritten LTV is higher on average than the original LTV, indicating that the agencies appraise the properties at a lower value than the originators. The reunderwritten DSCR and LTV also differ systematically across rating agencies—for example, S&P's DSCRs and LTVs both tend to be higher than its competitors'. However, the reunderwritten DSCR and LTV for the different agencies are not directly comparable, because the rating agencies employ different proprietary models, and may consider different "stress" scenarios.

[Table 1 goes about here.]

The regression in Table 2 shows the reduced-form relationship between AAA subordination and deal covariates and bidder-specific covariates that will feature in the structural model. All bidder-specific covariates in the regression are averaged over the winning bidders. The covariates include the weighted average original DSCR and LTV and deviations of the reunderwritten DSCR and LTV from the corresponding original values. I express the deviations as proportional "haircuts." That is, letting $DSCR_{il}^{orig}$ and LTV_{il}^{orig} denote the original DSCR and LTV for loan l in deal i, and letting $DSCR_{ijl}$ and LTV_{ijl} denote the corresponding reunderwritten values by agency j, the covariates in the regression are the averages over loans l and over the winning bidders j of the ratios $(DSCR_{il}^{orig} - DSCR_{ijl})/DSCR_{il}^{orig}$ and $(LTV_{ijl} - LTV_{il}^{orig})/LTV_{il}^{orig}$.[24]

A greater haircut on DSCR is associated with a significant increase in the AAA subordination, with a 5 percentage-point haircut (roughly one standard deviation) im-

single AAA tranche. During the peak of the real estate bubble, deals would often have two AAA-rated tranches—a so-called "super-senior AAA" tranche and a "junior AAA" tranche, the latter of which would be subordinate to the former. For my purposes, I define the AAA tranche as the aggregate of all tranches rated AAA, regardless of the names by which they are marketed.

[23] All averages over loans at the deal level are weighted by loan size.

[24] As shown in the table, I include an indicator controlling for the relatively rare event in which none of the reported rating agencies issues a pre-sale report, and set the haircuts equal to zero for these observations.

plying a 106 basis-point increase in the amount of subordination. This effect suggests that the AAA subordination at least partially incorporates the information contained in the haircuts. Haircuts on LTV have the same qualitative effect, although the effect is not statistically significant. The fact that the DSCR and LTV haircuts are not both significant is unsurprising, considering that the two haircuts are highly correlated.

Another key explanatory variable is the winning bidders' previous market share in rating recent deals. There are conceptual arguments for why the winning bidders' incumbency may be either positively or negatively correlated with AAA subordination. On the one hand, a bidder that has not won many recent deals may have an incentive to slacken its standards in order to compete harder for business. On the other hand, an agency with an established relationship with the current issuer based on prior deals may be more inclined to "cut a deal" with the issuer and give more lenient standards. Accordingly, I consider two alternative measures of incumbency. The first measure is each winning bidder's share of deals rated among the previous ten deals (by issuance date), averaged over the winning bidders.[25] An alternative measure, which would more directly capture the effect of deal-cutting based on an established relationship, is each winning bidder's share of deals rated among the previous three deals issued by the same bank as the current issuer. The evidence in the table suggests that incumbency is associated with less aggressive bidding. The estimates using the first measure (Column 1) indicate that an increase of 0.1 in the average winning bidder's share of the ten previous deals increases AAA subordination by 95 basis points. The estimates using the alternative measure (Column 2) are qualitatively similar.

Finally, note that, because an agency is more likely to win a deal when it requires less AAA subordination, incumbency is a lagged endogenous variable if the error in the regression is serially correlated over deals. I do not find much evidence of autocorrelation in the residuals.[26] Nevertheless, if there were positive serial correlation, it would imply that, if anything, the coefficients on the incumbency measure are biased in the negative direction, implying that the true coefficient on incumbency would be even stronger.

[25] Cohen and Manuszak (2013) use this measure as a proxy for the intensity of competition.

[26] I run the regression for each subsample of deals as defined by the identities of the winning bidder(s), and perform Durbin's alternative test for autocorrelation, sequencing the deals by their cutoff dates. Autocorrelation cannot be meaningfully be assessed in the case of deals with one winner due to the small sample size. When S&P and Moody's win, Fitch and Moody's win, or all three agencies win, I cannot reject the null hypothesis of no autocorrelation at the 5-percent significance level—and in the first and last cases, I obtain a p-value far in excess of 0.05. When S&P and Fitch win, and I cannot reject the null hypothesis of no autocorrelation at the 1-percent significance level.

[Table 2 goes about here.]

Table 3 shows proportional hazard regressions (Cox, 1972) for the timing of default for individual loans. The first purpose of this exercise is to show the relationship between AAA subordination and ex post loan performance. The unit of observation is an individual loan, and I define an event of default as occurring as soon as a loan is 60 or more days delinquent or is transferred into special servicing.[27] The explanatory variables include the AAA subordination for the deal containing the loan, with other loan characteristics as controls.[28] Greater AAA subordination is, unsurprisingly, a strong predictor of higher default: a 10-percentage point increase in subordination predicts an approximately 7.2-percent greater hazard.

The second purpose of this exercise is to see whether the pre-sale report variables have any explanatory power for ex post loan performance after controlling for AAA subordination. If so, this would indicate that the information contained in the pre-sale variables is not fully incorporated into AAA subordination, suggesting strategic behavior by the agencies. The regressors include the agencies' haircuts on DSCR and LTV for the individual loan (similar to the haircuts as defined in Tables 1 and 2 but computed at the loan level rather than aggregated as a deal weighted average). The estimates in Column 2 include a flexible control for AAA subordination in order to control for possible nonlinear effects that are correlated with the pre-sale variables.[29] Even after controlling for AAA subordination, the pre-sale report variables have predictive power for the ex post performance of loans. A 10-percent haircut on a loan's DSCR implies a 5.8 percent increase in the hazard of default. Likewise, a haircut on a loan's LTV also implies a greater hazard of default.

[27] In principle, default can also occur when the loan matures if the borrower is unable to pay the entire balloon payment. However, in the data we do not observe such "balloon defaults" because practically none of the mortgages matures during the sample period.

[28] If only a subset of the winning bidders report a reunderwritten DSCR or LTV for a particular loan, I take the average over that subset. The number of observations in the regression is somewhat lower than in the full sample due to missing observations for the explanatory variables.

[29] The regression includes restricted cubic splines, interpolating between 4 equally spaced percentiles of the distribution of AAA subordination. Alternatively, I ran the regression controlling for deciles of the AAA subordination, which yields a very similar result.

[Table 3 goes about here.]

Table 4 reports the results for a similar exercise to the previous one but looking at the performance of the entire deal rather than individual loans. The dependent variable is the sum of principal writedowns and interest payment shortfalls on the collateral pool as of the censoring date, expressed as a share of the original pool principal. The explanatory variables are AAA subordination, the haircuts on the weighted average DSCR and LTV (averaged over the winning bidders), and other deal covariates.[30] The controls include issuance-year dummies (to account for the fact that older deals have had more time over which to go bad), and the regression is specified as a tobit to account for the left-censoring of losses at 0. AAA subordination has the expected sign but is not statistically significant after controlling for other deal characteristics.[31] Similar to their effects at the individual loan level, the haircuts on DSCR and LTV predict worse ex post performance, even after controlling for AAA subordination, although only the haircut on LTV is significant at the 5 percent level due to the high degree of correlation between the two haircuts.

[Table 4 goes about here.]

4. MODEL

This section models rating agency and CMBS issuer behavior using an auction framework. The issuer of each deal $i = 1, \ldots, I$ acts as the auctioneer. The agencies are the bidders, and are indexed by $j = 1, \ldots, J$. There are three agencies (i.e., $J = 3$), representing S&P, Moody's, and Fitch. For reasons already discussed in the previous section,

[30]For parsimony, I do not include the various measures of pool diversification, which affects the volatility of returns and thus the expected losses on particular tranches, but not the expected loss on the overall pool.

[31]The loss of significance, relative to Table 3, is unsurprising considering the difference in unit of observation, because there are far fewer deals than loans.

I assume the bidder set is exogenous.

Auction setup and issuer decision rule

Issuer i solicits bids from the rating agencies. I discuss later how the rating agencies choose their bids, but for now, it suffices to define agency j's bid as a choice $b_{ij} \in [0, 1]$, which states the maximum proportion of the pool that the agency would allow the most senior debt tranche to comprise while still rating it "AAA." Equivalently, b_{ij} is 1 minus the minimum AAA subordination that bidder j would require. For example, a choice of $b_{ij} = 0.7$ states that agency j would give a AAA-rating to a bond backed by the most senior 70 percent of the pool principal, with 30 percent subordination. A choice of $b_{ij} = 0.8$ on the same deal would amount to a laxer requirement, because the AAA bondholders would only be protected from the first 20 percentage points of principal losses.

Given a bid profile $b_i \equiv \{b_{ij}\}_{j=1,...,J}$, the issuer chooses a subset of the bidders to publish their ratings. I indicate this choice by $d_i \in \{0, 1\}^J$, a J-by-1 vector of ones and zeros indicating the set of winners. The issuer must set the AAA tranche's proportion of the pool to $min\{b_{ij}|d_{ij} = 1\}$—that is, the lowest bid among those submitted by the winners. The actual bid that equals $min\{b_{ij}|d_{ij} = 1\}$ is the "pivotal" bid.[32]

For the base specification, I assume that the number of published ratings is exogenously determined, reflecting the "two-rating" industry norm, and view as anomalies the cases in which the observed number of ratings is one or three. I assume that the issuer cares about the relative proportions of the AAA versus the aggregate of the non-AAA tranches, with the issuer's profits being a monotone increasing function of the proportion of the AAA tranche. Although I do not explicitly model investor behavior, this particular assumption would hold if the AAA rating provides certification value, or if the investors have Bayesian beliefs and their valuation of the overall pool increases in the AAA tranche's proportion. The issuer therefore solves the following maximization for an auction with m winners:

$$(1) \qquad d_i(b_i) = \arg \max_{d_i, |d_i|=m} min\{b_{ij}|d_{ij} = 1\}$$

[32]For example, investors may observe that the AAA tranche comprises 70 percent of the pool and also observe the ratings by Moody's and Fitch, but they cannot observe whether Moody's or Fitch submitted the lower bid. "Split ratings"—where Moody's and Fitch's ratings on a particular tranche differ from each other—may occur for tranches other than the AAA tranche.

I also explore an alternative specification endogenizing the number of published ratings, for which I modify the issuer's maximization as follows:

$$(2) \qquad d_i(b_i) = \arg\max_{d_i} min\{b_{ij}|d_{ij} = 1\}[1 + \lambda_2 \mathbf{1}(\sum_j d_{ij} = 2) + \lambda_3 \mathbf{1}(\sum_j d_{ij} = 3)]$$

The form of this expression captures the fact that investors may place a premium on deals with more published ratings—either because they value corroborating opinions or because they are sophisticated and recognize issuers' incentive to rating shop. I do not explicitly model investor behavior, but rather, specify that the issuer's payoff depends in an exogenous way on the number of bids, with λ_2 representing the premium for having two ratings versus only one, and λ_3 representing the premium for having three ratings versus two. These premia counteract the issuer's incentive to choose fewer winners in order to maximize the AAA tranche's proportion.

Rating agencies' preferences

Each bidder j chooses its bid b_{ij} conditional on a belief t_{ij} about the loan pool quality for deal i, which is determined by the equation:

$$(3) \qquad t_{ij} = \beta_1' x_i + \beta_2' z_{ij} + u_{ij}$$

x_i is a vector of commonly observed deal covariates. The agency-specific component of the belief, $\beta_2' z_{ij} + u_{ij}$, depends on a vector of exogenous agency-specific covariates z_{ij} (the weighted-average reunderwritten DSCR and LTV at the deal level) and an idiosyncratic error u_{ij} that is independent of x_i and z_{ij}. The covariates z_{ij} and the error u_{ij} are agency j's private information at the time of bidding. However, the joint distribution of z_{ij} and u_{ij} across bidders is common knowledge. Agencies' valuations are affiliated through potential correlation of z_{ij} and u_{ij} across agencies. The exogeneity of z_{ij} is implied by the model's assumption that the reunderwritten DSCR and LTV are not chosen strategically, because the pre-sale reports are released after the auction is over and the deal structure has already been determined, implying that only the actual bids but not the pre-sale reports affect the agency's probability of winning.

Letting $d_{ij}(b_i)$ denote the j'th component of the issuer's decision vector $d_i(b_i)$, j's payoff given t_{ij} and a bid profile b_i is as follows:

$$\pi_j(t_{ij}, b_i) = d_{ij}(b_i)[1 - (\tau(b_{ij}) - t_{ij} - \beta_3 w_{ij})^2] \tag{4}$$
$$= d_{ij}(b_i)[1 - (\tau(b_{ij}) - \beta_1' x_i - \beta_2' z_{ij} - \beta_3 w_{ij} - u_{ij})^2]$$

The above expression normalizes the payoff from not winning ($d_{ij}(b_i) = 0$) to 0. The "1" inside the brackets normalizes the location of the payoff conditional on winning ($d_{ij}(b_i) = 1$). The payoff conditional on winning also depends on a loss from not bidding truthfully, captured by the squared term inside the expression, which I shall now explain. We can think of the bid b_{ij} as amounting to a nominal statement by j about the quality of the pool, with a higher bid conveying a more favorable statement. Because the nominal statement is strictly increasing in the bid, we can normalize it by a monotone increasing function $\tau(b_{ij})$. I discuss the specific choice of the function $\tau(\cdot)$ in the next subsection, but treat it as a known function for now. The deviation of $\tau(b_{ij})$ from the agency's true belief t_{ij} imposes a quadratic loss, which captures the agency's disutility from misrepresenting its beliefs. Conceptually, we can think of the disutility as stemming from damage to the agency's reputational stock.[33] The variable w_{ij} is the j's incumbency status—which I proxy by the share rated by j of the last three deals issued by the same bank as the current issuer—and is assumed to be common information. The associated parameter β_3 captures the effect of incumbency on the agency's willingness to distort the truth. For example, if agencies that have not rated many recent deals are willing to bid more aggressively, β_3 would be negative. β_3 would be positive if, instead, prior relationships between incumbents and issuers cause the incumbents to relax their standards and bid more aggressively.

The above specification of utility abstracts from common values: no agency has private information relevant to other agencies' expected utility, so there is no "winner's curse." Testing this assumption is beyond the scope of this paper but is addressed in separate work in progress. However, this assumption is weak for the following reason. To allow for common values, we would modify the model by treating t_{ij} as a noisy signal of j's true utility, which would be realized given the ex post performance of deal i. However, in CMBS, there is a great degree of noise in the ex post performance of the pool, which is realized stochastically far into the future due to the long maturity of the bonds, with a very low ex ante probability of an extreme outcome. Thus, even supposing there were a common values component, any winner's curse would be diffi-

[33] A dynamic framework that explicitly models reputation is outside the scope of this paper, but the quadratic loss can be thought of as the "reduced form" disutility implied by such a model.

cult for market participants to measure and would be heavily discounted in the ex ante payoffs. These features contrast with the typical common-value auction setting—such as auctions for oil and gas leases and procurement auctions—in which the ex post value of the good is easy to measure and is realized soon after the auction is held.[34]

It is also useful to point out the relationship between my utility specification and the specification of utility in a standard first-price auction for a good. For the latter, the net utility of a bidder j with a gross value v_j for the good, conditional on bidding b_j and winning the auction, is typically specified as $v_j - b_j$. That is, the disutility from paying the bid is assumed to be linear in b_i (reflecting risk-neutrality), with the price coefficient normalized to 1; the researcher's objective is typically to identify v_j. Here, we do the reverse: we normalize the gross value to 1, and our goal instead is to identify the disutility from the bid, which depends on the latent term t_{ij}. Instead of assuming that the effect of the bid on utility is linear (which would be unrealistic in the current setting), we instead assume that it is quadratic in the deviation of $\tau(b_{ij})$ from t_{ij}.

Using $w_{i,-j}$ to denote the incumbency status of the competing bidders, optimal bidding by agency j's implies the following first-order condition:

$$
\begin{aligned}
(5)\qquad \tfrac{\partial E[\pi_j(t_{ij},b_i)|x_i,w_{i,-j},z_{ij}]}{\partial b_{ij}} = 0 = \tfrac{\partial E[d_{ij}(b_i)=1|x_i,w_{i,-j},z_{ij}]}{\partial b_{ij}}&[1-(\tau(b_{ij})-t_{ij}-\beta_3 w_{ij})^2] \\
+E[d_{ij}(b_i)=1|x_i,w_{i,-j},z_{ij}]&[-2(\tau(b_{ij})-t_{ij}-\beta_3 w_{ij})\cdot\tau'(b_{ij})]
\end{aligned}
$$

Solving the first-order condition implies j's true belief t_{ij}. The first-order condition has two roots, and we use the second-order condition to identify the correct root, which satisfies $(\tau(b_{ij}) - t_{ij} - \beta_3 w_{ij}) > 0$.

4.1. *Normalization of mapping from beliefs to bids*

The private belief t_{ij} implied by (5) is identified up to the choice of $\tau(\cdot)$, the monotone transformation normalizing the nominal statement corresponding to the choice of b_{ij}. To the extent that we only care about the ordinal ranking of t_{ij} across deals, this choice is without loss of generality. However, the choice of $\tau(\cdot)$ affects the functional form of the relationship between the belief and covariates, which is linear in equation (3).

For the empirical implementation, I derive $\tau(b_{ij})$ by imputing the loss distribution for the pool that would be consistent with a AAA-rating for a senior security with subordination $1 - b_{ij}$, based on what the rating agencies purport to be the expected

[34]Haile et al (2012) and Somaini (2013) are among many such examples.

loss associated with a "AAA" rating. In particular, Moody's asserts that for structured finance securities, AAA implies an "idealized loss rate" of 0.001 percent within the first four years.[35]

I parametrize the loss distribution for the pool by assuming that losses follow a transition process over time that is described by a reflected Brownian motion, which is standard in the literature on asset pricing.[36] Losses begin at 0 at the deal issuance date and are reflected at zero, such that they are constrained to always be non-negative. If the volatility parameter of the Brownian motion is σ, the cumulative distribution of losses through time t is given by $\Phi(y/(\sqrt{t}\sigma)) - \Phi(-y/(\sqrt{t}\sigma))$, with density $2/(\sqrt{t}\sigma) \cdot \phi(y/(\sqrt{t}\sigma))$, where $\Phi(\cdot)$ and $\phi(\cdot)$ denote the cumulative distribution and density of the standard normal distribution. Letting $\tau \equiv -log(\sigma)$, I define $\tau(b_{ij})$ implicitly as the value of τ such that a senior security with subordination $1 - b_{ij}$ has an expected loss over 4 years equal to the rating agencies' "idealized loss rate" for AAA over the same amount of time:

$$
\begin{aligned}
(6) \qquad \tau(b_{ij}) \quad \equiv \quad \tau : & \int_{1-b_{ij}}^{1} \frac{y-(1-b_{ij})}{b_{ij}} \cdot \frac{2}{\sqrt{4}exp(-\tau)} \cdot \phi(\frac{y}{\sqrt{4}exp(-\tau)})dy \\
& = \text{“idealized loss rate” on AAA over 4 years}
\end{aligned}
$$

The greater is τ, the lower the volatility of the loss transition process, and by the above formula the lower the expected loss on the AAA security, implying higher quality.

[35] See "Probability of Default Ratings and Loss Given Default Assessments for Non-Financial Speculative-Grade Corporate Obligors in the United States and Canada," Moody's Investors Service (August 2006), Appendix 1 (available online). Each Moody's rating purportedly corresponds to a range of values for the *expected loss* on the bond. S&P and Fitch follow a different methodology, and their ratings purportedly correspond to ranges of values for the *probability of default* on the bond, irrespective of the loss given default or the total distribution of losses. In practice, the ratings of the three major rating agencies are largely viewed by investors as being interchangeable in terms of what they imply about credit risk, so I treat the S&P and Fitch ratings as representing the same range of "idealized" expected losses as the corresponding Moody's rating.

[36] As a robustness check, I alternatively modeled the loss distribution using the beta distribution with α as the first parameter and $\tau(b_{ij})$ as the log of the second parameter. A beta distribution is unimodal when the second parameter is > 1, with the mean and mode of the distribution declining in the second parameter for a given value of the first parameter).

4.2. *Identification*

This section first discusses how the joint distribution of agencies' equilibrium bids is identified by the data. After identifying the equilibrium bidding behavior, agencies' true beliefs are implied by the optimality condition (5).[37] Although my setup does not have a second-price auction format, for the following reason, we can identify the bid distribution by exploiting previously established identification results for second-price auctions with private values. In a standard second price auction with private values, bidders optimally bid their true values, implying that the conditions for identifying the value distribution in that setting are equivalent to the conditions necessary for identifying a bid distribution.

A well-known *non*-identification result is that, with data consisting only of bids, second price auctions with unrestricted private values are not identified unless all bids are observed. This data requirement is clearly not satisfied here because we only observe the pivotal bid determining AAA subordination. Dropping i subscripts and letting $b^{(j:J)}$ denote the jth order statistic for a sample of bids $b = (b_1, \dots b_J)$, the pivotal bid is given by $b^{(J-K+1:J)}$ when there are K winners. However, even when only a subset of the order statistics of the bids is observed, identification is restored if there are bidder-specific covariates with sufficient variation (Theorem 5 in Athey and Haile, 2002). In my setting, the bidder-specific covariates for j comprise the weighted-average reunderwritten DSCR and LTV at the deal level, z_{ij}, and the incumbency measure, w_{ij}.

Collecting the incumbency terms $w_i \equiv \{w_{ij}\}_{j=1,\dots,J}$, we can represent agency j's equilibrium bid function as:

$$b_{ij} = \Phi(g_i(x_i, w_i, z_{ij}) + \varepsilon_{ij}), \quad j = 1, \dots, J. \tag{7}$$

Φ is a known monotone transformation, which I choose without loss of generality to be the standard normal CDF (which constrains the bids to be between 0 and 1). By assumption, ε_{ij} is independent of (x_i, w_i, z_{ij}). Let $d_i^* \equiv \{d_{ij}^*\}_{j=1,\dots,J}$ denote the observed set of winners and let b_i^* denote the (observed) pivotal bid. The function $g_i(x_i, w_i, z_{ij})$ is identified by the observed relationship between b_i^* and the covariates (x_i,w_i, z_{ij}) in the information sets of the winning bidders $j|d_{ij}^* = 1$.[38] The intuition for how the

[37] In common with much of the literature, I assume that the bid data are generated by a single equilibrium.

[38] We can equivalently think of $g_i(x_i, w_i, z_{ij})$ as being identified in the limit for values of $z_{ij'}|(d_{ij'}^* = 0)$ such that $g_i(x_i, w_i, z_{ij'}) \to -\infty$.

distribution of $(\varepsilon_{i1}, \ldots, \varepsilon_{iJ})$ is identified is as follows. For the time being, suppose that all of the bidder-specific covariates (w_{ij} and z_{ij}) were observed for all bidders. Then, when bidder j is in the observed set of losers ($d^*_{ij} = 0$), the distribution of ε_{ij} is traced out by variation over auctions in the covariates w_{ij} and z_{ij}, given the condition $\Phi(g_i(x_i, w_i, z_{ij}) + \varepsilon_{ij}) < b^*_i$. Similarly, when j is in the observed set of winners ($d^*_{ij} = 0$), the distribution of ε_{ij} is traced out by variation in w_{ij} and z_{ij}, given the condition $\Phi(g_i(x_i, w_i, z_{ij}) + \varepsilon_{ij}) \geq b^*_i$.[39] With sufficient variation in the z's and w's, the entire joint distribution of $(\varepsilon_{i1}, \ldots, \varepsilon_{iJ})$ is identified.

One complication is that the reunderwritten DSCR and LTV are only observed for the winning bidders. Suppose j is a winning bidder and j' is a losing bidder, such that z_{ij} is observed but $z_{ij'}$ is unobserved. However, the distribution of $z_{ij'}$ conditional on the observed value of z_{ij} is identified from *other* auctions in which both j and j' are among the winners. That is, because the reunderwritten DSCR and LTV for different rating agencies are jointly distributed, their observed values for a winning bidder j are informative about their values for a losing winning bidder j'. The identification argument in the paragraph following expression (7) continues to hold with the slight modification that $z_{ij'}$ for $j'|d_{ij'} = 0$ is known up to a conditional distribution as opposed to being completely observed.

Once the joint distribution of agencies' equilibrium bids is identified, we can identify the bidders' beliefs straightforwardly. Because our purpose is ultimately to identify the extent to which the equilibrium deal structure is distorted, we are primarily interested in the beliefs of the pivotal bidders. If the identity of the pivotal bidder is known to be j (i.e., when there is a single winner), the value of $(t_{ij} - \beta_3 w_{ij})$ can be identified by solving the optimality condition (5), setting b_{ij} to b^*_i. The relationship between x_i,w_{ij}, z_{ij}, and b^*_i (which has a monotone relationship with the difference $t_{ij} - \beta_3 w_{ij}$) identifies the parameters β_1, β_2, and β_3, from which we can identify t_{ij} by netting out $-\beta_3 w_{ij}$ from $(t_{ij} - \beta_3 w_{ij})$.[40]

For auctions with two or three winners, the pivotal bidder's belief is an unobserved random variable whose value depends on which of the winners is pivotal. If we *knew* that the pivotal bidder is j, we could solve for t_{ij} in the same way as described in the previous paragraph. Obviously, with more than one winner, we cannot in fact know with

[39] In the case of auctions with one winner, this weak inequality is an equality, allowing us to completely identify ε_{ij} for the winning bidder j.

[40] The case in which agencies' beliefs are serially correlated, which would makes one of the elements of z_{ij} (the incumbency measure) endogenous, is dealt with in a robustness check.

certainty whether j is pivotal. However, we can compute the posterior probability of j being the pivotal bidder, given equilibrium bidding behavior, and form an expectation of the pivotal player's belief. I describe this step in greater detail in the following section.

4.3. *Estimation*

The estimation procedure closely mirrors the identification arguments, and falls under the general class of two-step estimators described in the literature that includes papers such as Bajari, Benkard, and Levin (2007) and Bajari, Hong, Krainer, and Nekipelov (2010). In the first step, I estimate the joint distribution of equilibrium bids as a function of observable covariates, and also estimate the joint distribution of the reunderwritten variables (z_{ij}). In the second step, I recover an expectation of the pivotal bidder's belief by solving the optimality condition (5), setting $b_{ij} = b_i^*$ for each winning bidder j, and taking an expectation over the implied beliefs.

First-step estimation

In estimation, I approximate $g_i(\cdot)$ in the equilibrium bid function using a sieve representation. Specifically, I modify expression (7) as follows:

$$b_{ij} = \Phi(\pi_i' h(x_i, w_i, z_{ij}) + \varepsilon_{ij}) \tag{8}$$

The vector $h(x_i, w_i, z_{ij})$ comprises splines and interactions among the covariates in j's information set.[41] Although the equilibrium bid distribution is nonparametrically identified, for parsimony, I assume that the idiosyncratic error ε_{ij} is jointly normally distributed across bidders with variance Ω.

Collecting terms, let the vector z_i^* denote the observed values of z_{ij} (reunderwritten DSCR and LTV) for the winning bidders. I assume that the deviations of the reunderwritten DSCR and LTV from the original DSCR and LTV are jointly normally distributed across rating agencies, with mean μ_z and covariance Ω_z.

Letting $\theta \equiv (\pi, \Omega, \mu_z, \Omega_z)$ and letting $f(b_i^*|d_i^*, \theta, x_i, w_i, z_i^*)$ denote the conditional density of the equilibrium pivotal bid, we can estimate θ by maximizing the likelihood:

$$L(d^*, b^*|\theta, x, w, z) = \sum_i log[f(b_i^*|d_i^*, \theta, x_i, w_i, z_i^*) \cdot Pr(d_i^*|\theta, x_i, w_i, z_i^*)] \tag{9}$$

[41] Assuming the policy functions are nonparametric, consistency requires that the number of sieve basis functions increase at a known rate with respect to the total number of observations.

Because the regions of integration for the unobservables (the ε_{ij}'s and the z_{ij}'s for the non-winning bidders) are extremely complex, I simulate the distribution of the unobservables using Gibbs sampling.[42]

Structural estimation

To estimate the structural parameters, I begin by solving the optimality condition (5) for each observed winner j to obtain the belief that would rationalize j's bidding $b_{ij} = b_i^*$, which I denote by $t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta)$. The argument θ makes explicit the dependence of $t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta)$ on the first-step parameters, which determine j's equilibrium beliefs about its competitors' bid distributions.

For auctions with one winner, the identity of the pivotal bidder j is known, so $t_{ij} = t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta)$. For auctions with two or three winners, I construct the expectation of the pivotal bidder's belief by taking the expectation of $t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta)$ over all winning bidders, weighting by the posterior probability (given equilibrium bidding behavior and observables) of each bidder being the pivotal one:

$$\begin{aligned}
\bar{t}_i &\equiv \sum_{j|d_{ij}^*=1} t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta) Pr(\text{j pivotal in auction } i|\ d_i^*, b_i^*, \theta, x_i, w_i, z_i^*). \\
&= \sum_{j|d_{ij}^*=1} t_{ij}(b_i^*, x_i, w_i, z_{ij}, \theta) Pr(b_{ij} = b_i^*, b_{ij'} < b_i^*\ \forall j' \text{ s.t. } j' \neq j \ \&\ d_{ij'}^* = 1 \mid d_i^*, b_i^*, \theta, x_i, w_i, z_i^*).
\end{aligned}$$

Taking expectations of equation (3) over the same posterior probabilities and plugging in $\bar{t}_i$ gives us the expected value of the residual:

$$\begin{aligned}
&\bar{u}_i \equiv \bar{t}_i - \beta_1' x_i - \beta_2' \bar{z}_i, \text{ where} \\
&\bar{z}_i \equiv \sum_{j|d_{ij}^*=1} z_{ij} Pr(b_{ij} = b_i^*, b_{ij'} < b_i^*\ \forall j' \text{ s.t. } j' \neq j \ \&\ d_{ij'}^* = 1 \mid d_i^*, b_i^*, \theta, x_i, w_i, z_i^*)
\end{aligned}$$

I estimate the parameters by means of the generalized method of moments, exploiting the conditions $E[\bar{u}_i x_i] = E[\bar{u}_i w_{ij}] = E[\bar{u}_i \bar{z}_{ij}] = \mathbf{0}$.

[42] ε_{ij} is observed for the winning bidder for auctions with one winner. The unobservables comprise ε_{ij} for all non-winners in auctions with one winner, ε_{ij} for all bidders in auctions with multiple winners, and the reunderwritten DSCR and LTV for non-winners. In practice, I assume that $\pi_i' h(x_i, w_i, z_{ij})$ is separable into two components, $\pi_i' h(x_i, w_i, z_{ij}) = \pi_{i1}' h_1(x_i, w_i) + \pi_{i2}' h_2(z_{ij})$, implying that for non-winning bidders, the components $\pi_{i2}' h_2(z_{ij}) + \varepsilon_{ij}$ can be simulated as a single unobservable. At each step of the Gibbs sampling, I draw each unobservable from a truncated distribution that is consistent with the observables $(d_i^*, b_i^*, x_i, w_i, z_i^*)$, conditional on the remaining unobservables.

The condition $E[\bar{u}_i w_{ij}] = 0$ requires that the incumbency measure w_{ij} be exogenous, which in turn requires that the idiosyncratic error in j's belief, u_{ij}, be serially uncorrelated.[43] Serial correlation in u_{ij} seems unlikely given the lack of serial correlation in the residuals of the reduced-form regression for AAA subordination (see note 26 and accompanying text). Nevertheless, as a robustness check, I can also estimate the model without imposing the condition $E[\bar{u}_i w_{ij}] = 0$, which is feasible because the sufficient dimensionality of the "instruments" (w_{ij}, z_{ij}) provides us with overidentifying restrictions.

Finally, note that, having identified the equilibrium bid distribution and the parameter β_3, we can also simulate the entire joint distribution of agencies' beliefs. For simulation draw s, we draw a bid profile $b_i^{(s)}$ from the equilibrium bid distribution. Then, for each bidder j, we can compute the belief $t_{ij}^{(s)}$ that rationalizes j's simulated bid $b_{ij}^{(s)}$, taking as given the equilibrium bidding behavior of j's competitors. The full distribution of bidders' beliefs is given by the joint distribution of $\{t_{ij}^{(s)}\}_{j=1,\dots J}$.

5. RESULTS

First-step estimates

Estimates for the joint distribution of the reunderwritten variables z_{ij} (parametrized by μ_z and Ω_z) and the equilibrium bidding behavior (parametrized by π and Ω) are reported in Tables 5 and 6, respectively. The estimates of S&P's mean reunderwritten DSCR and LTV are each higher than those of the other agencies, which is consistent with the differences across agencies in the raw means (Table 1). The covariance (Ω_z) estimates indicate that the reunderwritten DSCR and LTV are strongly correlated across rating agencies, especially the reunderwritten LTV. The reunderwritten DSCR and LTV by a given agency are negatively correlated with each other, indicating that an agency's degree of pessimism (relative to the original underwriting) tends to be consistent between the two characteristics.

[Tables 5 and 6 go about here.]

[43] Serial correlation would imply that incumbency for bidder j would be positively correlated with j's belief about the current deal. Failure to take into into account this source of endogeneity would make j appear to distort its bid more than it actually does by placing a downward bias on the value of t_{ij} imputed from the optimality condition (5).

Because there are only 591 deals in the final sample,[44] my empirical specification of the bid function includes only linear terms in the sieve basis. I augment the agency-specific covariates for j with a dummy variable for the relatively rare case in which j is an observed winner but does not produce a pre-sale report.[45] The point estimates (Table 6) are intuitively sensible. Bids are lower for pools containing more loans with balloon payments and for larger deals. Although in theory cross-collateralization diversifies the risk of individual loans, the negative coefficient on it could reflect the agencies' taking into account nonrandom selection of riskier borrowers into cross-collateralized loans. Higher pool concentration by originator and property type is associated with lower bids, although the coefficients on the various HHI measures are difficult to interpret individually because the various concentration measures are highly correlated. As expected, an agency's bid tends to be higher when the agency's reunderwritten DSCR and LTV are higher and lower, respectively. The vintage fixed effects indicate that from 2000 until around 2003 or 2004, the overall trend was toward more aggressive bidding.[46] The initial time trend implies a 7.2 percentage point increase in the bid over this time period.[47] This trend completely unwound during the crisis years of 2005-2007, when the agencies became far more conservative. However, in 2010, the bids became more aggressive once again. Finally, the estimates of the covariance matrix Ω indicate a high degree of correlation across bidders in the unexplained component of the bid (ε_{ij}), which is unsurprising given that bidding behavior probably depends on commonly observed deal covariates that I do not observe in the data.

Because identifying the structural parameters requires having first-stage estimates that fit the data accurately, I perform two exercises to assess the fit of the first-step estimates, which I report in Appendix A. First, I compare the model predictions for various outcomes with their empirical counterparts. As shown in the Appendix, the

[44]I drop a few deals from the sample because of missing deal-level data or because a significant share of loans in the pool have missing data.

[45]The likelihood does not condition the simulated distribution of the losing bidders' reunderwritten DSCR and LTV on the "missing" values of z_{ij} for the winners in these cases.

[46]There was virtual no origination activity during 2008 and 2009, so both here as well as in all other cases in which I include year fixed effects, I pool the 2008 originations with the 2007 originations, and the 2009 originations with the 2010 originations.

[47]Evaluated relative to a baseline setting the AAA tranche's proportion to the sample mean of 0.796.

predicted frequency with which each agency is a winner matches the data quite well. The mean of the predicted pivotal bid also matches the data remarkably well for various cuts of the data. The sample variance of the predicted pivotal bid is somewhat lower than its empirical counterpart, but not by much.

Second, to address potential concerns about overfitting, I assess the out-of-sample fit. Specifically, I use half of the sample for estimation, then use the resulting estimates to predict the bidding behavior and identity of the winners for the other half of the sample (the validation sample), and compare these predicted values to their empirical counterparts. As shown in the Appendix, the model fit for the validation sample is slightly worse than the within-sample fit. However, the mean and standard deviation of the pivotal bid continue to match the data remarkably well.

Appendix B shows estimates for the alternate specification that endogenizes the number of winners, using the characterization of the issuer's decision rule in (2).[48] In principle, the issuer's premia on having at least two ratings (λ_2) or three ratings (λ_3) are identified by the relative frequency of auctions for which there are one, two, or three winners. However, because the z_{ij}'s for losing bidders are known only in distribution, we have only weak identification of λ_2 and λ_3 separately from the degree of correlation in the bids.[49] Intuitively, both greater correlation in the bids and a greater issuer premium on publishing more ratings would tend to result in more winners being selected. To finesse this issue, I do not attempt to estimate λ_2 and λ_3. Rather, I fix their values at a level that is *higher* than seems reasonable (5 percent and 2.5 percent respectively)—which maximally alters the likelihood function for the remaining parameters, relative to the base specification in which the number of winners is exogenous. Therefore, if the number of winners were truly endogenous, the difference between these alternative estimates and the baseline estimates would "bound" the impact of assuming an exogenous number of winners. In fact, I do not find much difference between the two specifications, except that the coefficients on the bidder-specific covariates (β_2) are somewhat greater in magnitude when we endogenize the number of winners.[50]

[48]Endogenizing the number of winners affects the likelihood function (9) by imposing additional limits on the support for the bidders' unobservables.

[49]The correlation in the bids is determined by the covariance matrix Ω and the relative magnitudes of the coefficients for the deal covariates, β_1, versus the coefficients for the agency-specific covariates, β_2.

[50]Note that greater correlation in agencies' bids reduces the "penalty" to the issuer of choosing more winners. The intuition for why the magnitude of the β_2 coefficients goes up when we endogenize the number of winners is that, when we allow for an exogenous premium on deals with multiple winners,

[Tables 7 and 8 go about here.]

Structural estimates

Figure 1 superimposes two distributions. The first is the sample distribution of $\bar{t}_i$, the expectation of the pivotal bidder's belief (weighting each winning bidder j by the probability that j is pivotal). The second one is the sample distribution of $\tau(b_i^*)$, the nominal statement about quality implied by the pivotal bid b_i^*. The distribution of $\tau(b_i^*)$ is shifted to the right relative to the distribution of $\bar{t}_i$, with the difference between the two distributions indicating the extent of ratings distortion due to strategic bidding.

To give more intuition for the magnitude of this distortion, we can compute the expected losses on the AAA tranche implied by taking $\bar{t}_i$ to be the true volatility parameter of the loss transition process for each deal i.[51] Averaging over deals, the mean implied expected loss on the AAA tranche is 3.70 percent, corresponding to the Moody's "idealized loss" for a "Baa3" rating.[52]

When I estimate the model without imposing the moment condition $E[\bar{u}_i w_{ij}]$, the implied values of $\bar{t}_i$ are extremely similar to the base specification. The mean and standard deviation of $\bar{t}_i$ under this alternative specification are -.291 and .390, respectively, compared with .247 and .373 for the base specification, and the value of $\bar{t}_i$ has a correlation of 0.9653 across the two specifications.

Table 7 reports estimates of β_1, β_2, and β_3, the coefficients for the covariates of the belief t_{ij}; and the covariance matrix for $\{u_{ij}\}_{j=1,\ldots,J}$, the idiosyncratic component of t_{ij}.[53] The table reports both the base specification and specification that endogenizes

it is possible to rationalize the presence of such deals with a lower degree of correlation in the bids.

[51] I set the volatility parameter of the Brownian motion transition process to $exp(-\bar{t}_i)$.

[52] The standard deviation across all auctions is 1.46×10^{-2}, respectively. The difference in order of magnitude between the probabilities implied by the bids versus the true beliefs is unsurprising. The probability of the AAA tranche experiencing positive losses is highly nonlinear in the volatility of the underlying pool, implying that a small difference in the volatility parameter can imply a large difference in the probability of positive losses.

[53] Standard errors must be bootstrapped to reflect the first-step estimation error. Doing so time-consuming and is currently in progress.

the number of winning bidders.[54] As expected, the idiosyncratic belief u_{ij} is correlated across bidders. The estimated values of β_1, β_2, and β_3 are reassuringly consistent with the reduced-form effect of each covariate on equilibrium AAA subordination (Table 2)—at least among those that are statistically significant in both sets of estimates. For example, a greater share of loans with balloon payments and greater concentration (less diversification) in property-types are negatively correlated with the belief t_{ij}, just as they are positively correlated with AAA subordination in the reduced-form regression. The vintage dummies indicate a declining trend in the agencies' beliefs between the peak of the real estate bubble in 2004 and the beginning of the crisis in 2007, and a subsequent improvement after the crisis in 2010. Turning to the agency-specific covariates, a higher reunderwritten DSCR and lower reunderwritten LTV are each correlated with a higher belief, as expected. The coefficient on incumbency is negative, suggesting that winning previous auctions makes bidders bid less aggressively, but is not significant at the 5 percent level.

[Table 7 goes about here.]

Table 8 decomposes the nominal statement conveyed by the pivotal bid for deal i, $\tau(b_i^*)$, and shows how the various components change over time. I decompose $\tau(b_i^*)$ into a component of beliefs explained by commonly observed deal characteristics ($\beta_1' x_i$), along with expectations (weighting each winning bidder j by the probability that j is pivotal) of the following: the component of beliefs explained by agency-specific covariates ($\beta_2' \bar{z}_i$); the idiosyncratic component of beliefs ($\bar{u}_i$); and the distortion between the pivotal bid and true beliefs ($\tau(b_i^*) - \bar{t}_i$).

The table reports this decomposition, averaging over auctions by year.[55] The main discernible trends are that the common component of beliefs peaked in 2004, then fell

[54]Note that endogenizing the number of winners affects the relationship between an agency's bid and the probability of winning, which enters the expectation terms on the right-hand side of the first-order condition (5).

[55]For the purposes of reporting in the table, I decompose the reunderwritten DSCR and LTV (z_{ij}) each into two parts: the original DSCR or LTV and the deviation between agency j's reunderwritten DSCR or LTV and the original value. I include the original values in the common component and the deviation in the agency-specific component.

leading up to the crisis in 2007, and that the component of beliefs explained by agency-specific covariates trended downward over time. Overall, the distortion due to strategic bidding accounts for about a quarter of the nominal statement.

[Table 8 goes about here.]

6. TESTABLE IMPLICATIONS: EX POST BOND PERFORMANCE AND EX ANTE BOND PRICING

As an additional check for the plausibility of the structural analysis, we can assess testable implications using independent data sources other than those used to estimate the model. First, I exploit data on the ex post performance of the bonds, and ask whether bidders' true beliefs have predictive power for ex post performance, after flexibly controlling for the equilibrium AAA subordination. Conceptually, the true beliefs should have informational content because the equilibrium AAA subordination is not fully revelatory about the bidders' private information: observing the AAA subordination is equivalent to observing only the pivotal bid, which is only an order statistic of the full set of bids.

Table 9 shows tobit regressions for the sum of principal writedowns and interest payment shortfalls as a share of the original pool principal—the same dependent variable as in Table 4. The key explanatory variable is the expectation of the pivotal bidder's belief, $\bar{t}_i$. In the first column, I control for the number of winning bidders and include flexible (nonparametric) controls for the pivotal bid (b_i^*), which captures the information contained in the equilibrium AAA subordination. I also run the regression separately for subsamples of the data depending on the identities of the auction winners (Columns 2–4), in case these identities are informative.[56] I find that the true beliefs are a significant predictor of ex post losses. The estimates in Column 1 imply that an increase in the expected belief equal to one standard deviation (across deals) in the amount of distortion (.295) is associated with a 4-percentage point decrease in the realized loss. For comparison, the sample average for the ex post loss on the pool is 2.43 percentage points.

[56] I only report the results for auctions with two winners, because there are too few observations for the remaining cases.

Subsampling by the identity of the winning bidder shows that this result is driven by deals rated by S&P and Fitch and by Moody's and Fitch.

[Table 9 goes about here.]

Another testable implication is that the expected belief of the pivotal bidder should influence the pricing of the CMBS securities if investors are sophisticated about how ratings are determined.[57] In Table 10, the dependent variable is the yield at the time of issuance for a set of CMBS securities,[58] which I regress on the expected belief ($\bar{t}_i$) and flexible controls for AAA subordination.[59] I perform the regression separately for bonds in different rating categories, and also control for the bond maturity, the current market-wide average yield on outstanding bonds of a similar rating as of the time of deal issuance (which controls for time variation in bond yields), pool size, measures of pool diversification (HHI), and fixed effects for each CMBS-issuing bank.[60]

Beliefs do not have a statistically significant effect on the pricing of AAA-rated bonds, which is unsurprising given that the AAA tranche is the least informationally sensitive tranche. However, higher beliefs are associated with a strong and significant decrease in yield for bonds rated AA and below. The coefficient of -635 for AA and A-rated bonds indicates that an increase in the expected belief equal to one standard deviation in the amount of distortion predicts a 187 basis-point decrease in yield for AA and A-rated bonds. Likewise, the coefficient of -1399 for BBB-rated bonds indicates that an increase in the expected belief equal to one standard deviation in the amount of distortion predicts a 413 basis-point decrease in yield for bonds rated BBB and below. It thus appears that investors at least partially account for the ratings distortion.

[57] Because the investors observe the pre-sale data, they could, at least in theory, replicate the exercise performed in this paper.

[58] I only have initial pricing for a subset of the CMBS securities, because many of the securities were privately placed. I omit deals issued during 2007 due to the extreme volatility of the overall bond market during the crisis.

[59] All yields are expressed as a spread over the Treasury yields for the maturity of the bond.

[60] For example, I have a fixed effect for Credit Suisse and another for Bank of America, each of which is associated with multiple CMBS deals i. The fixed effects capture potential pricing effects associated with particular banks.

[Table 10 goes about here.]

7. COUNTERFACTUALS

Because we identify the distribution of agencies' beliefs, we can examine counterfactual outcomes and simulate the effects of various proposed policy reforms. The key challenge to performing counterfactual analysis is that we must compute the bidding behavior under the new equilibrium.

For simplicity, I consider only pure-strategy Nash equilibria (PSNE). Appendix C argues that a PSNE exists for this game and, furthermore, that if we discretize the set of possible bids and take the limit for successively finer action sets, the equilibrium of the discretized game converges to the equilibrium given a continuous set of possible bids. I operationalize this result by discretizing the action space for auction i into a set of A_i bid increments. A bidder j's strategy can thus be characterized by a set of A_i cutoff types, which I denote by the vector X_{ij}. Collecting terms, the entire strategy profile can be summarized by the cutoffs for all J bidders by $X_i \equiv X_{i1}, \ldots, X_{iJ}$. I denote the best-response correspondence to this strategy profile by $\Gamma(X_i)$, and solve for an equilibrium by finding a fixed point of Γ.[61]

RESULTS – IN PROGRESS.

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Figure 1: Sample distributions of $\bar{t}_i$ (expectation of pivotal bidder's true belief, weighting each winning bidder j by probability that j is pivotal) and $\tau(b_i^*)$ (nominal statement implied by pivotal bid)

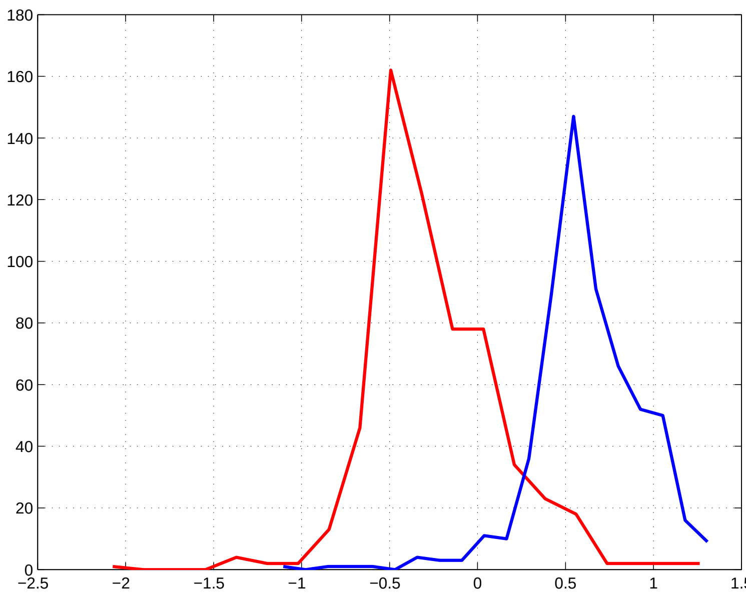

Figure depicts the density of the sample distribution of $\bar{t}_i$, the expectation of the pivotal bidder's true belief taken over the set of observed winners (weighting each winner by the conditional probability that it is the pivotal bidder, given equilibrium bidding behavior) and the density of the sample distribution of $\tau(b_i^*)$, the nominal statement about pool quality implied by the pivotal bid.

Table 1: Summary Statistics - deal characteristics

	Mean	Std Deviation
Rating outcomes		
AAA subordination	0.204	0.060
S&P rated deal	0.701	
Moody's rated deal	0.705	
Fitch rated deal	0.581	
Deal covariates		
Weighted-average loan characteristics		
Balloon payment	0.951	0.138
Cross-collateralization	0.162	0.204
Original DSCR	1.507	0.277
Original LTV	0.677	0.067
Loan balance ($M)	15.915	11.316
Originated by deal issuer	0.467	0.349
Concentration indices (HHI) for loan characteristics		
By originator	0.550	0.249
By property type	0.324	0.156
By region	0.239	0.238
By MSA	0.146	0.264
By loan's share of pool balance	0.031	0.029
Pool total principal ($B)	1.591	1.132
Ex post performance of pool		
Principal writedown and interest shortfall as proportion of original principal, as of June 2011	0.024	0.026

	Mean	Std Deviation
S&P bidder-specific covariates		
produced pre-sale report, conditional on rating deal	0.928	
reunderwriten DSCR (weighted average for deal)	1.457	0.207
reunderwriten LTV (weighted average for deal)	0.835	0.158
share rated among last 10 deals	0.707	
share rated among last 3 deals by same bank	0.695	
Moody's bidder-specific covariates		
produced pre-sale report, conditional on rating deal	0.722	
reunderwriten DSCR (weighted average for deal)	1.350	0.288
reunderwriten LTV (weighted average for deal)	0.792	0.160
share rated among last 10 deals	0.700	
share rated among last 3 deals by same bank	0.705	
Fitch bidder-specific covariates		
produced pre-sale report, conditional on rating deal	0.955	
reunderwriten DSCR (weighted average for deal)	1.362	0.255
reunderwriten LTV (weighted average for deal)	0.778	0.142
share rated among last 10 deals	0.581	
share rated among last 3 deals by same bank	0.566	

N = 613

Table 2: AAA Subordination Regressions (OLS)

	(1)		(2)	
	Estimate	Std error	Estimate	Std error
Pool characteristics at cutoff - weighted averages over loans				
Balloon payment	0.118	0.031	0.124	0.031
Cross-collateralization	0.009	0.014	0.014	0.014
Original DSCR	-0.030	0.012	-0.027	0.012
Original LTV	0.019	0.050	0.057	0.047
Originated by deal issuer	0.020	0.011	0.021	0.011
Pool characteristics at cutoff - concentration indices (HHI)				
By originator	-0.012	0.011	-0.014	0.011
By property type	0.191	0.027	0.199	0.026
By region	-0.098	0.069	-0.074	0.069
By MSA	0.054	0.064	0.029	0.063
By loan's share of pool balance	0.593	0.180	0.672	0.179
Other deal characteristics				
Pool total principal	0.009	0.003	0.009	0.003
No pre-sale reports available	0.002	0.014	-0.002	0.015
Deal rated by 3 agencies	0.027	0.009	0.025	0.009
Deal rated by 1 agency	-0.028	0.013	-0.019	0.013
Vintage dummies	Included		Included	
Bidder-specific variables, averaged over winning bidders				
Wtd avg haircut on DSCR*	0.211	0.033	0.206	0.033
Wtd avg haircut on LTV*	0.021	0.023	0.020	0.024
Share of last 10 deals	0.095	0.022		
Share of last 3 deals by same bank			0.032	0.013
N	576		577	
R-squared	0.957		0.956	

Table shows regression of AAA subordination (as proportion of pool principal) on deal-level covariates.
Weighted average haircuts are averages over loans l and over winning bidders j of the following:

(original $DSCR_l$ - $DSCR_l$ as reunderwritten by j)/(original $DSCR_l$), and

(LTV_l as reunderwritten by j - original LTV_l)/(original LTV_l).

Table 3: hazard regressions for loan default time

	Hazard ratio	Std error	Hazard ratio	Std error
	(1)		(2)	
Loan characteristics at deal cutoff date				
Loan seasoning	1.014	0.001	1.014	0.001
Original DSCR	0.744	0.044	0.746	0.044
Occupancy	0.131	0.015	0.132	0.015
No occupancy data	0.134	0.015	0.134	0.015
Original LTV	32.604	5.271	32.447	5.249
Coupon spread	1.512	0.032	1.513	0.032
Original loan amount	2.262	0.127	2.251	0.126
Interest-only loan	1.211	0.044	1.211	0.044
Fixed-rate mortgage	0.511	0.092	0.465	0.087
Insurance co. loan	0.737	0.037	0.738	0.037
I-bank loan	1.136	0.030	1.135	0.030
Domestic conduit loan	1.358	0.075	1.361	0.075
Finance co. loan	0.996	0.047	0.995	0.047
Foreign conduit loan	1.247	0.033	1.242	0.033
Characteristics of deal containing the loan				
AAA subordination (linear effect)	2.009	0.750		
Splines for AAA subordination			Included	
No pre-sale reports available	0.655	0.065	0.675	0.067
Bidder-specific variables, averaged over winning bidders				
Haircut on DSCR for loan	1.377	0.208	1.384	0.210
Haircut on LTV for loan	1.361	0.165	1.318	0.161
Fixed effects				
Loan origination year	Included		Included	
Loan origination month	Included		Included	
Region and property-type (interacted)	Included		Included	
N	59433		59433	

Table shows Cox proportional hazard regressions for individual loans' default times.
Dependent variable is the time to default, defined as the time between loan origination and the point at which the loan is 60 days delinquent or in special servicing.
Haircuts on DSCR and LTV for loan l are averages over winning bidders j of the following:

(original $DSCR_l$ - $DSCR_l$ as reunderwritten by j)/(original $DSCR_l$), and

(LTV_l as reunderwritten by j - original LTV_l)/(original LTV_l).

Table 4: Tobit regression for principal losses and interest shortfall on deal

	Estimate	Std error	Estimate	Std error
Pool characteristics at cutoff - weighted averages				
Balloon payment	-0.0570	0.0111	-0.0582	0.0112
Cross-collateralization	-0.0060	0.0058	-0.0059	0.0058
Original DSCR	-0.0056	0.0049	-0.0064	0.0050
Original LTV	0.1692	0.0185	0.1612	0.0201
Originated by deal issuer	-0.0061	0.0042	-0.0058	0.0042
Other deal characteristics				
Pool total principal	-0.0048	0.0013	-0.0048	0.0013
No pre-sale reports available	-0.0098	0.0058	-0.0091	0.0058
Deal rated by 3 agencies	0.0020	0.0038	0.0023	0.0038
Deal rated by 1 agency	-0.0107	0.0054	-0.0107	0.0054
AAA subordination (linear effect)	0.0393	0.0225		
Splines for AAA subordination			Included	
Deal vintage dummies	Included		Included	
Bidder-specific variables, averaged over winning bidders				
Wtd avg haircut on DSCR	0.0007	0.0143	0.0010	0.0144
Wtd avg haircut on LTV	0.0277	0.0097	0.0265	0.0099
Square-root of error variance	0.0222	0.0007	0.0222	0.0007
N	577		577	

Dependent variable is sum of principal loss and interest payment shortfalls on the deal's loan pool, as of the censoring date, expressed as a share of the original pool principal.

Letting ψ denote the linear coefficient and ε a normal error, the assumed model is:

$$(\textit{dependent variable}) = \psi'(\textit{covariates}) + \varepsilon \text{ if } \psi'(\textit{covariates}) + \varepsilon > 0$$

Table 5: first-step estimates: distribution of reunderwritten DSCR and LTV - base specification

Means (μ_z)

	S&P		Moody's		Fitch	
	DSCR	LTV	DSCR	LTV	DSCR	LTV
Mean	-0.0759	0.2419	-0.3059	0.2074	-0.2627	0.1813
Std error of mean	0.0310	0.0077	0.0245	0.0088	0.0247	0.0080

Covariances (Ω_z)

		S&P		Moody's		Fitch	
		DSCR	LTV	DSCR	LTV	DSCR	LTV
S&P	DSCR	0.0923					
	LTV	-0.0033	0.0121				
Moody's	DSCR	0.0401	-0.0005	0.0837			
	LTV	0.0034	0.0114	-0.0053	0.0177		
Fitch	DSCR	0.0522	-0.0010	0.0487	-0.0019	0.0604	
	LTV	0.0027	0.0115	-0.0054	0.0156	-0.0032	0.0165

Standard errors of covariance

		S&P		Moody's		Fitch	
		DSCR	LTV	DSCR	LTV	DSCR	LTV
S&P	DSCR	0.0070					
	LTV	0.0039	0.0011				
Moody's	DSCR	0.0062	0.0052	0.0123			
	LTV	0.0042	0.0024	0.0041	0.0015		
Fitch	DSCR	0.0051	0.0045	0.0060	0.0033	0.0046	
	LTV	0.0049	0.0021	0.0041	0.0016	0.0038	0.0017

Tables shows maximum likelihood estimates of the joint distribution of the weighted-average reunderwritten DSCR and LTV for each agency (at the deal-level), assuming joint normality.
The weighted averages are demeaned by the weighted-average original DSCR and LTV, respectively.
Parameters are jointly estimated with those reported in Table 6, but only reported separately due to space considerations.

Table 6: first-step estimates: bid functions -- base specification

Sieve parameters (π)	**Coefficient**	**Standard error**
Agency fixed effects		
S&P	1.1984	0.0035
Moody's	1.1974	0.0085
Fitch	1.1972	0.0058
Common covariates		
Balloon payment (wtd avg)	-0.3077	0.0099
Cross-collateralization (wtd avg)	-0.0897	0.0138
Pool total principal	-0.0394	0.0047
Originator HHI	-0.0938	0.0097
Property type HHI	-0.5491	0.0059
Region HHI	0.2982	0.0152
Deal vintage fixed effect:		
2001	0.0889	0.0225
2002	0.0167	0.0113
2003	0.2937	0.0164
2004	0.2914	0.0126
2005	-0.0038	0.0110
2006	-0.0592	0.0112
2007	-0.0633	0.0167
2010	0.0694	0.0134
Bidder-specific covariates		
Share of last 3 deals by same bank	-0.0007	0.0022
Reunderwritten DSCR	0.0089	0.0065
Reunderwritten LTV	-0.0088	0.0109
Bidder produced no pre-sale report	0.0057	0.0122

Covariance of idiosyncratic error (Ω), point estimates

	S&P	Moody's	Fitch
S&P	0.0131		
Moody's	0.0125	0.0133	
Fitch	0.0124	0.0125	0.0130019

Standard errors of covariance of idiosyncratic error

	S&P	Moody's	Fitch
S&P	0.0006		
Moody's	0.0003	0.0009	
Fitch	0.0004	0.0006	0.000749

Table shows "first-step" estimates of the agencies' equilibrium bidding behavior.
Sieve parameters capture the effect of covariates on bidding behavior for individual agencies.
Covariance parameters capture the joint distribution of agencies' bids that is not explained by covariates.
Parameters are jointly estimated with those reported in Table 5, but only reported separately due to space considerations.

Table 7: Structural Estimates

	Baseline specification			Endogenizing number of winners, setting $\lambda_2 = .05$ and $\lambda_3 = .025$		
Common covariates (β_1)	**Coefficient**	**Std error**		**Coefficient**	**Std error**	
Constant	3.8422	0.4779		5.3396	0.3252	
Balloon payment (wtd avg)	-0.8661	0.3424		-1.2739	0.2487	
Cross-collateralization (wtd avg)	-0.2004	0.1291		-0.1523	0.0907	
Pool total principal	0.0616	0.0236		-0.0455	0.0135	
Originator HHI	-0.0566	0.0749		-0.2076	0.0690	
Property type HHI	-0.6892	0.3044		-1.2074	0.1625	
Region HHI	1.0388	0.1894		0.7477	0.1532	
Deal vintage fixed effects:						
2001	-0.0141	0.0535		0.1692	0.0490	
2002	-0.0783	0.0589		0.0498	0.0395	
2003	0.2149	0.0677		0.5046	0.0775	
2004	0.2858	0.0578		0.4864	0.0562	
2005	-0.0889	0.0730		0.0734	0.0621	
2006	-0.1007	0.0834		0.0864	0.0748	
2007	-0.0245	0.0825		0.0802	0.0723	
2010	0.0040	0.0793		0.1297	0.0807	
Bidder-specific covariates (β_2 and β_3)						
Share of last 3 deals by same bank	-0.1866	0.1420		-0.2471	0.1244	
Reunderwritten DSCR	0.2028	0.1636		0.3416	0.1143	
Reunderwritten LTV	-0.7123	0.2333		-0.0946	0.2519	
Bidder produced no pre-sale report	-0.7482	0.1637		-0.2292	0.1421	
Covariance of residual u_{ij}	Moodys	S&P	Fitch	Moodys	S&P	Fitch
Moodys	0.1445	0.0779	0.0511	0.0745	0.0665	0.0625
S&P	0.0779	0.1658	0.0468	0.0665	0.0945	0.0694
Fitch	0.0511	0.0468	0.1366	0.0625	0.0694	0.0825

N = 591

Table shows estimates of the structural parameters that determine the relationship between observed covariates and bidders' beliefs.
Residual u_{ij} is computed by simulating distribution of beliefs for the full set of bidders and netting out the effects of the covariates.

Table 8: Decomposition of nominal statement implied by pivotal bid

Mean of components over deals, by vintage

Vintage	Belief component due to common covariates ($\beta_1'x_i$)	--- Expectations weighting bidder *j* by probability that *j* is pivotal Belief component due to agency-specific covariates ($\beta_2'\ \bar{z}_i$)	Idiosyncratic signal ($\bar{u}_i$)	Rating distortion ($\tau(b_i*) - \bar{t}_i$)	Share of nominal statement attributable to distortion
2000	3.033	-0.319	-0.062	0.916	0.257
2001	2.989	-0.292	-0.020	0.974	0.267
2002	2.960	-0.318	0.015	0.900	0.253
2003	3.238	-0.297	0.063	0.943	0.239
2004	3.391	-0.367	0.004	0.922	0.233
2005	3.031	-0.438	0.016	0.888	0.254
2006	3.037	-0.454	-0.002	0.836	0.245
2007	3.114	-0.535	0.002	0.781	0.232
2010	3.006	-0.451	0.096	0.981	0.270

Standard errors of means, by vintage

Vintage	Belief component due to common covariates ($\beta_1'x_i$)	--- Expectations weighting bidder *j* by probability that *j* is pivotal Belief component due to agency-specific covariates ($\beta_2'\ \bar{z}_i$)	Idiosyncratic signal ($\bar{u}_i$)	Rating distortion ($\tau(b_i*) - \bar{t}_i$)
2000	0.041	0.041	0.052	0.042
2001	0.030	0.025	0.025	0.001
2002	0.023	0.017	0.037	0.028
2003	0.022	0.017	0.054	0.024
2004	0.030	0.021	0.034	0.023
2005	0.033	0.020	0.046	0.033
2006	0.032	0.020	0.042	0.038
2007	0.034	0.021	0.044	0.048
2010	0.029	0.028	0.049	0.001

Table decomposes $\tau(b_i*)$, the nominal statement about pool quality for deal *i*, as implied by the pivotal bid, into common and agency-specific components explained by model covariates (Columns 1 and 2), an idiosyncratic agency-specific component (Column 3), and the distortion relative to agencies' true signals (Column 4). Columns 2, 3, and 4 are expectations over the winning bidders, weighting each bidder by the posterior probability of that bidder being the pivotal one.

Table 9: Tobit regressions of ex post deal outcomes (principal writedown plus interest shortfall as percentage of original pool principal) on expected belief of pivotal bidder and controls.

	Full sample		Rated by S&P and Moody's		Rated by S&P and Fitch		Rated by Moody's and Fitch	
	(1)		(2)		(3)		(4)	
	Estimate	Std error	Estimate	Std error	Estimate	Std error	Estimate	Std error
Expected belief ($\bar{t}_i$)	***-0.1360***	0.0575	0.0717	0.0642	***-1.3065***	0.2438	-0.7946	0.6272
Deal rated by 3 agencies	***0.1294***	0.0562						
Deal rated by 1 agency	0.0007	0.0058						
Deciles for AAA subordination*	Included		Included		Included		Included	
Vintage dummies	Included		Included		Included		Included	
Square-root of error variance	0.0218	0.0007	0.0159	0.0008	0.0232	0.0014	0.0153	0.0010
N	379		158		116		74	

Dependent variable is sum of principal loss and interest payment shortfalls on the deal's loan pool, as of the censoring date, expressed as a share of the original pool principal.

Letting ψ denote the linear coefficient and ε a normal error, the assumed model is:

$$(\textit{dependent variable}) = \begin{cases} \psi'(\textit{covariates}) + \varepsilon & \text{if } \psi'(\textit{covariates}) + \varepsilon > 0 \\ 0 & \text{otherwise} \end{cases}$$

Table 10: Regression of bond yields at issuance on
on expected belief of pivotal bidder and controls

	AAA-rated		AA and A		BBB and below	
	Estimate	Std error	Estimate	Std error	Estimate	Std error
Maturity (months)	0.04	0.03	0.15	0.03	0.04	0.07
Market-average yield on similarly rated outstanding bonds	2.13	0.24	2.25	0.15	1.50	0.20
Share of pool with balloon payment*	55.75	28.44	31.24	30.75	82.57	69.83
Average cross-collateralization*	-8.34	11.53	-3.52	8.92	-29.62	26.18
Pool total principal	-5.74	2.56	2.03	2.03	-9.36	5.99
Pool HHI by originator	-4.13	9.41	-1.65	7.49	14.43	21.28
Pool HHI by property type	-40.81	36.18	-9.18	29.29	-187.51	82.76
Pool HHI by region	19.91	71.07	104.80	53.74	425.37	145.27
Expected belief ($\bar{t}_i$)	212.37	335.43	-634.91	179.92	-1399.10	524.95
Deal rated by 3 agencies	-204.88	327.29	618.64	176.06	1376.43	512.93
Deal rated by 1 agency	26.19	27.04	-18.20	23.67	-29.34	67.45
Rated "A"			18.51	2.79		
Rated "BBB"					168.72	23.41
Deciles for bond subordination amount	Included		Included		Included	
Fixed effects by issuer name	Included		Included		Included	
N	295		1220		808	

Dependent variable is bond spread at issuance over Treasury yield of same maturity as the bond.
"Market-average yield on similarly rated outstanding bonds" is the spread over the Treasury yield for previously issued CMBS bonds of similar remaining maturity, and captures time series variation in CMBS yields.

* Weighted averages over loans

APPENDIX A: WITHIN-SAMPLE AND OUT-OF-SAMPLE FIT FOR FIRST-STEP ESTIMATES

[Appendix A table goes about here.]

APPENDIX B: FIRST-STEP ESTIMATES FOR ENDOGENOUS NUMBER OF WINNERS

[Tables B.1 and B.2 go about here.]

APPENDIX C: EXISTENCE OF PURE STRATEGY NASH EQUILIBRIUM

In this Appendix, I argue informally that a pure-strategy Nash Equilibrium exists for the bidding game described in the model. If the possible set of actions were discrete (e.g., if bidders could only bid in increments of 0.01), the existence of a PSNE would be guaranteed so long as the game satisfies the Single-Crossing Condition (SCC) and certain other regularity conditions (see Definition 3 and Theorem 1 in Athey (2001)). The SCC can easily be shown to hold in our setup, and stipulates that, for each player $j = 1, \ldots, J$, whenever every opponent $j' \neq j$ uses a strategy that is nondecreasing in its type, player j's objective function satisfies the *single crossing property of incremental returns* in (b_{ij}, t_{ij}). Because the objective function $\pi_j(t_{ij}, b_i)$ is differentiable, it suffices to show that $\frac{\partial \pi_j(t_{ij}, b_i)}{\partial t_{ij} \partial b_{ij}} > 0$.

In the case of continuous actions, existence of a PSNE could be shown constructively by taking the limit of the finite-action equilibrium for successively finer action sets *if* the limit of this series were guaranteed to be an equilibrium of the continuous game. A complication arises in bidding games, such as in our setup, because the outcome (namely, the set of winners) is discontinuous in the actions. However, this problem goes away if, in the limit as the action set gets fine, "mass points" do not arise and the payoffs are continuous. The conditions for this to hold are discussed in Theorem 6 of Athey (2001), and are either standard or hold trivially in the current setting by virtue of the assumption of private values.

Appendix A. Within- and out-of-sample Fit

Within-sample fit, frequency of each bidder being among the auction winners

	S&P among winners	**Moody's among winners**	**Fitch among winners**
Empirical mean	0.7208	0.7191	0.5905
Predicted mean[(a)]	0.7812	0.6537	0.5956

Within-sample fit, mean and standard deviation of pivotal bid (b_i *) over sample of auctions

Subsample definition	**Empirical mean**	**Predicted mean**	**Empirical std deviation**	**Predicted std deviation**[(b)]
Full Sample	0.7603	0.7634	0.0791	0.0625
S wins in data	0.8443	0.8397	0.0611	0.0598
M wins in data	0.8304	0.8183	0.0755	0.0653
F wins in data	0.7537	0.7740	0.0905	0.0566
S, M win in data	0.7592	0.7646	0.0836	0.0645
S, F win in data	0.7639	0.7609	0.0681	0.0570
M, F win in data	0.7650	0.7646	0.0623	0.0539
S, M, F win in data	0.7650	0.7646	0.0623	0.0539
2000-2003 vintages	0.7811	0.7814	0.0593	0.0479
2004-2007 vintages	0.7497	0.7532	0.0894	0.0751
2010 vintage	0.7560	0.7592	0.0624	0.0425

Table shows fit statistics for the baseline model specification. A unit of observation is an auction. Bottom panel summarizes predicted and empirical pivotal bids for the full sample and for various subsamples defined by the set of winning bidders in the data.

(a) Mean over all deals *i* of (predicted expectation of *j* being a winner of *i*).
(b) Standard deviation over all deals *i* of (pivotal bid based on one simulated draw of the bids).

Out-of-sample fit for validation sample, frequency of each bidder being among the auction winners

	S&P among winners	Moody's among winners	Fitch among winners
Empirical mean	0.7199	0.7092	0.5709
Predicted mean[(a)]	0.7225	0.5330	0.7445

Out-of-sample fit for validation sample,
mean and standard deviation of pivotal bid (b_i*) over sample of auctions

Subsample definition	**Empirical mean**	**Predicted mean**	**Empirical std dev**	**Predicted std deviation**[(b)]
Full Sample	0.7608	0.7656	0.0773	0.0650
S wins in data	0.8270	0.8374	0.0865	0.0477
M wins in data	0.8238	0.8143	0.0872	0.0684
F wins in data		No observations		
S, M win in data	0.7626	0.7682	0.0792	0.0648
S, F win in data	0.7640	0.7607	0.0651	0.0607
M, F win in data	0.7583	0.7652	0.0600	0.0523
S, M, F win in data	0.7583	0.7652	0.0600	0.0523
2000-2003 vintages	0.7831	0.7809	0.0528	0.0462
2004-2007 vintages	0.7532	0.7585	0.0902	0.0748
2010 vintage	0.7518	0.7584	0.0642	0.0512

Table shows out-of-sample fit statistics for the validation sample after estimating the baseline model on a random 50-percent sample of the data. Bottom panel summarizes predicted and empirical pivotal bids for the full sample and for various subsamples defined by the set of winning bidders in the data.

(a) Mean over all deals *i* of (predicted expectation of *j* being a winner of *i*).
(b) Standard deviation over all deals *i* of (pivotal bid based on one simulated draw of the bids).

Table B.1: first-step estimates: distribution of reunderwritten DSCR and LTV
Endogenizing number of winners, setting λ_2 = .05 and λ_3 = .025

Means (μ_z)

	S&P		Moody's		Fitch	
	DSCR	LTV	DSCR	LTV	DSCR	LTV
Mean	-0.0800	0.2465	-0.3072	0.2121	-0.2631	0.1852
Std error of mean	0.0316	0.0080	0.0242	0.0093	0.0243	0.0085

Covariances (Ω_z)

		S&P		Moody's		Fitch	
		DSCR	LTV	DSCR	LTV	DSCR	LTV
S&P	DSCR	0.0924					
	LTV	-0.0033	0.0121				
Moody's	DSCR	0.0400	-0.0004	0.0836			
	LTV	0.0034	0.0114	-0.0054	0.0176		
Fitch	DSCR	0.0522	-0.0011	0.0486	-0.0017	0.0604	
	LTV	0.0028	0.0116	-0.0058	0.0155	-0.0031	0.0164

Standard errors of covariance

		S&P		Moody's		Fitch	
		DSCR	LTV	DSCR	LTV	DSCR	LTV
S&P	DSCR	0.0044					
	LTV	0.0032	0.0011				
Moody's	DSCR	0.0035	0.0031	0.0086			
	LTV	0.0044	0.0023	0.0038	0.0015		
Fitch	DSCR	0.0047	0.0033	0.0054	0.0032	0.0039	
	LTV	0.0044	0.0019	0.0038	0.0016	0.0037	0.0017

Tables shows maximum likelihood estimates of the joint distribution of the weighted-average reunderwritten DSCR and LTV for each agency (at the deal-level), assuming joint normality.
The weighted averages are demeaned by the weighted-average original DSCR and LTV, respectively.
Parameters are jointly estimated with those reported in Table B.2, but only reported separately due to space considerations.

Table B.2: first-step estimates: bid functions

Endogenizing number of winners, setting λ_2 = .05 and λ_3 = .025

Sieve parameters (π)	**Coefficient**	**Standard error**
Agency fixed effects		
S&P	1.1783	0.0106
Moody's	1.1746	0.0104
Fitch	1.1737	0.0086
Common covariates		
Balloon payment (wtd avg)	-0.2949	0.0189
Cross-collateralization (wtd avg)	-0.0914	0.0208
Pool total principal	-0.0366	0.0078
Originator HHI	-0.0913	0.0190
Property type HHI	-0.5411	0.0291
Region HHI	0.2248	0.0243
Deal vintage fixed effect:		
2001	0.0922	0.0348
2002	0.0149	0.0171
2003	0.2955	0.0238
2004	0.2963	0.0192
2005	0.0067	0.0189
2006	-0.0443	0.0186
2007	-0.0402	0.0274
2010	0.0698	0.0223
Bidder-specific covariates		
Share of last 3 deals by same bank	0.0044	0.0072
Reunderwritten DSCR	0.0026	0.0188
Reunderwritten LTV	-0.1216	0.0184
Bidder produced no pre-sale report	0.0381	0.0116

Covariance of idiosyncratic error (Ω), point estimates

	S&P	Moody's	Fitch
S&P	0.0193		
Moody's	0.0188	0.0203	
Fitch	0.0185	0.0190	0.0198

Standard errors of covariance of idiosyncratic error

	S&P	Moody's	Fitch
S&P	0.0008		
Moody's	0.0006	0.0009	
Fitch	0.0006	0.0007	0.0008

Table shows "first-step" estimates of the agencies' equilibrium bidding behavior.
Sieve parameters capture the effect of covariates on bidding behavior for individual agencies.
Covariance parameters capture the joint distribution of agencies' bids that is not explained by covariates.
Parameters are jointly estimated with those reported in Table B.1, but only reported separately due to space considerations.