Competition and Credit Ratings After the Fall

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Abstract

We analyze the entry of new credit rating agencies into structured finance products. Our setting is unique as we study a period in which the incumbents' reputation was extremely poor and the benefit of more fee income from inflating ratings was low. We find entrants cater to issuers by issuing higher ratings than incumbents, particularly for interest-only (IO) tranches. Using measures of market share that are exogenous to incumbent ratings, we provide suggestive evidence that incumbent rating levels become more generous as entrant market share in a product type increases. We also exploit a feature of structured finance that identifies rating shopping and find that incumbent ratings increase in shopping.

JEL: G18, G21, G24, G28.

1 Introduction

High quality credit ratings can reduce informational asymmetries and transactions costs in financial markets. Credit ratings provided by a third party can be particularly helpful in encouraging participation in financial market activities among investors that are less likely to collect their own information (see Boot and Thakor (1993) for a discussion of market segmentation by information sensitivity). Conversely, low quality credit ratings can lead to dysfunction in financial markets. Indeed, Mathis, McAndrews, and Rochet (2009), Ashcraft, Goldsmith-Pinkham, and Vickery (2010), and Griffin and Tang (2012) have documented the role of the credit rating agencies (CRAs) in the dysfunction that led to a collapse in structured finance products in the 2007-2009 period. A large literature from other asset classes has also shown that credit ratings have meaningful effects on real economic outcomes.[1] Given the central role that CRAs play in financial markets, several entities including the SEC (2011, 2012) have suggested that one way to improve credit ratings is to enable greater competition. Indeed, the Credit Rating Agency Reform Act of 2006 required the SEC to increase competition among CRAs (SEC 2013). In the spring of 2012, European regulators also implemented a framework to increase competition between CRAs (Kanter 2012).

To better understand how rating agencies compete and the effects of competition on ratings, we study the entry of two firms into the market for commercial mortgage-backed securities (CMBS) ratings. Our setting is unique given that (1) the entrants did not initially rate corporate, municipal, or sovereign bonds,[2] and (2) the upheaval in the structured finance market in recent years resulted in a significant loss of reputation for incumbent CRAs.

We find that the entrants issue systematically higher ratings, often by several notches, than established CRAs. The entrants' average ratings are higher than those of each of

[1]See, for example, Alp (2013), Baghai, Servaes, and Tamayo (2014), Adelino and Ferreira (forthcoming), Almeida, Cunha, Ferreira, and Restrepo (forthcoming), and Cornaggia, Cornaggia, and Israelson (2014). See Cornaggia, Cornaggia, and Israelson (2014) for a review of the extensive earlier literature on the real effects of credit ratings.

[2]One of the entrants intends to rate corporate bonds and has very recently begun rating public finance bonds, but over our sample period was primarily active in CMBS. The other entrant rates only structured finance.

the three main incumbents, and this phenomenon is not due to unobserved heterogeneity in security quality. The difference between entrant and incumbent ratings is especially pronounced in interest-only (IO) tranches, which the entrants rate AAA almost uniformly. The entrants' ratings are still significantly higher in the non-IO sample although the economic magnitude of the difference is much smaller for these securities. The gap between entrant and incumbent ratings is higher for the entrant that is struggling more to gain market share, and it is also higher shortly after entry by the CRA that does gain significant market share. Taken together, the findings suggest that higher entrant ratings are part of a strategy to win business from the incumbents. However, it does not appear this strategy is sufficient to gain a dominant market position.

We further find that entry affects the level of the incumbents' ratings. Our main variable of interest is the percentage of securities of a particular CMBS deal type ("conduit/fusion," "large loan," and "other" deal types) issued in a given year that are rated by the entrants. By simultaneously controlling for the year of issuance and the deal type, as well as time trends, we do not capture merely that CMBS ratings became more lax over time, or that some deal types are rated more leniently. To further mitigate endogeneity and other selection concerns, we generate predicted entrant market shares that are exogenous to the level of incumbent ratings. While we cannot completely rule out selection explaining some of the increase in incumbent ratings, our results using these predicted shares suggest that some of the relationship between entrant shares and incumbent ratings is causal rather than solely reflecting the ability of entrants to choose markets in which incumbent rating levels are already increasing.

We find that as the entrants' market share in a deal type increases, the ratings assigned by incumbents are more favorable from the perspective of the issuer. A 10 percentage point increase in the share of non-IO securities rated by an entrant raises the average incumbent rating by about 0.3 notches. As the entrants' total combined market share is 52% by the end of our sample period, this represents an economically meaningful increase in the favorability of incumbent ratings. Consistent with more generous incumbent ratings, we also find that an increase in the entrants' share lowers the level of subordination for securities rated AAA by at least one incumbent. These results hold when we use the predicted entrant shares as explanatory variables.

The finding that the ratings of the incumbents increase in the entrants' market share could be due to rating shopping on the part of issuers, rating catering on the part of the CRAs, or a combination of both. Rating shopping occurs when issuers seek multiple ratings in an attempt to find the most favorable ones. Rating catering refers to the CRAs courting business by using lax standards. Theoretical work shows that competition always exacerbates shopping and often exacerbates catering. However, no empirical work to date has attempted to distinguish between these two mechanisms or measure their relative impact on rating levels. We show that no one agency had close to 100% market share in the CMBS market, thus leaving scope for both shopping and catering.

Rating shopping is never explicitly disclosed, so we exploit a unique feature of the structured finance market - the interdependence of securities within a given deal - and create two measures of shopping. Our more conservative measure considers a deal to be "shopped" when alternate tranches are missing ratings from different CRAs, with no change in the total number of ratings, a structure which 6% of the deals in our sample exhibit. Both our measures increase following entry, and one of the measures is consistently statistically significant in explaining the change in incumbent ratings in response to changes in entrant shares.

The remainder of the paper proceeds as follows. The next section discusses the institutional setting, explains theoretical predictions about and previous empirical work on the effect of competition on ratings, and relates this work to our setting. Section 3 presents our shopping measures and data. Section 4 discusses the ratings of the entrants. In Section 5, we estimate the effect of entry on the ratings of the incumbents, and Section 6 concludes.

2 Background and Hypotheses

2.1 Institutional Setting

To better understand the catering and shopping mechanisms and the extent to which the intensity of each varies across security types, a brief overview of the institutional details in the structured finance rating market is useful. See An, Deng, and Gabriel (2011) and Titman and Tsyplakov (2010) for descriptions of the CMBS market more generally.

Structured finance issuers, like other types of issuers, seek ratings in order to (1) provide investors with information about the risk of loss of value and (2) to satisfy investors' demand for regulatory certification. The key difference between the rating process in structured finance as compared to that in, e.g., corporate debt, is what is being *rated* vs. what is being *evaluated*. For corporate debt these are one and the same—a CRA evaluates default risk for a security and then issues a rating. In structured finance, however, the individual securities are part of a larger deal, and the cash flows and risks associated with a particular security are usually related to its position in the deal relative to the other securities. This means that the CRA must evaluate the entire deal structure in order to generate ratings for most individual securities. Thus, although the market observes *security*-level ratings, CRAs conduct *deal*-level analysis to produce those ratings.

There are usually multiple AAA tranches in a CMBS deal. One reason for this is to satisfy different maturity appetites such that there are multiple top tranches that differ by the schedule on which they are to receive principal payments. This allows the issuer to create low-risk securities with expected maturities of, say, 3, 5, and 7 years.[3] Rating a structured finance security typically begins by determining the subordination level for the highest tranches in the capital structure (e.g., the tranches that will receive AAA ratings). This process involves an informal, back-and-forth discussion between the CRA and the issuer

[3]Prepayment risk on CMBS is small since the majority of securitized commercial mortgages have defeasance clauses (see Dierker, Quan, and Torous 2005). Therefore, the main source of risk is the credit risk of the collateral.

that centers on how the issuer can maximize the portion of the deal that is rated *AAA*. Importantly, determining the top tranches' subordination levels requires a CRA to analyze the underlying collateral for the deal, but does not require it to analyze the remainder of the deal structure (the waterfall) since, by definition, the top tranches are the first to receive principal and interest payments.

However, if an issuer wants ratings for securities in a deal with, say, three tranches, a CRA must analyze and rate the first and second in order to rate the third. This is because rating a security that lies below others in the waterfall requires an analysis of the interest and principal cash flows that the waterfall promises to the tranches above it. More generally, to rate tranche n in the capital structure, a CRA must conduct enough analysis to also rate tranche $n-1$. In other words, the CRA must analyze the deal structure in order to rate a given security. Shopping for ratings for mezzanine or junior securities necessarily implies that a CRA must also analyze (and more or less rate) the portion of the deal structure that is senior. In such a case it may be more accurate to characterize shopping as occurring at the *deal* level.

The requirement that CRAs analyze an entire deal structure in order to rate securities below the most senior makes the concept of rating shopping more nuanced in structured finance than in corporate debt. Whereas shopping is a security-level phenomenon in corporate bonds, it cannot be thought of as such in structured finance. From the perspective of a CRA, rating a structured finance deal involves a substantial investment of resources and it seems unlikely that the issuer can see the actual rating of every security in the deal before it decides whether to buy each one. It is more likely that it gets a preliminary opinion from a CRA on certain aspects of the deal and then decides whether to proceed with further negotiations. If the threat of unsolicited ratings is sufficiently strong, some of the shopping will be disclosed in the form of an additional rating.[4] However, it is also possible that, so long as the issuer purchases ratings for enough of the securities in the deal, it can choose *not*

[4]Fulghieri, Strobl, and Xia (2014) suggest that CRAs issue unsolicited ratings precisely to deter shopping.

to buy the ratings on only one or two tranches.

Another unique aspect of structured finance is the existence of a class of securities known as interest-only (IO) that have very different features, rating methodology, and investor bases than non-IOs. The IO tranches are created by stripping off the spread between the weighted average collateral coupon and the coupon on the securities with principal balances. Securitizing this spread allows the issuer to immediately monetize the profit from deal issuance, rather than waiting to accumulate the profits over the life of the deal. IOs are not trivial in terms of volume in CMBS: they represent 20% of the number of tranches in our sample, and 38% of the dollar amount of trading volume (primary and secondary market) in CMBS is in IO and Principal Only (PO) tranches.[5] IOs have no principal balance by definition. Thus, they lack features, such as subordination and weighted average life, CRAs use as part of the rating process for non-IOs. The result is that some CRAs publish separate methodologies for this class of securities.

Additionally, IO investors tend to be more sophisticated investors with the ability to conduct the same type of risk analysis as CRAs. Our conversations with market participants indicate that IO investors are more likely to be hedge funds, dealers, and money managers than large insurance companies or pension funds. Thus, they may not use IO ratings for the information they contain, but merely for the regulatory certification, either internal or external, that they provide. Even among institutions that are not subject to government-mandated ratings-based regulatory requirements, internal controls usually require reporting a rating on any security held. Such investors would likely have a preference for higher ratings regardless of whether they believe the ratings are accurate.

[5]We calculate the share of IOs and POs in CMBS trading using FINRA aggregate trading volume data for structured products for 2011-2014 as tabulated by SIFMA (2014a).

2.2 Competition and product quality: what are the effects and what are the channels?

While competition is generally thought to improve product quality in most economic settings, ratings are unusual because the main consumers are investors while the purchasers are issuers. Similar settings include vehicle emissions testing and auditing of financial statements.[6] Because the buyers and consumers of ratings have different goals, it is not obvious from either a theoretical or empirical standpoint that increased competition should lead to higher rating quality.

Much of the theory on ratings in particular (e.g., Bolton, Freixas, and Shapiro 2012, Camanho, Deb, and Liu 2012, and Frenkel 2015) suggests that, under the issuer-pays fee scheme, the effect of competition depends on the reputation of the incumbents.[7] In particular, Camanho, Deb, and Liu (2012) show that more competition can actually lead to more accurate ratings when the reputations of both the incumbent and the entrant are low. Intuitively, this occurs because the possibility of gaining market leadership when reputations are similar is higher than if one CRA has a much better reputation than the other. Since market leadership is "up for grabs," both CRAs have an incentive to rate accurately and make incremental gains in reputation and therefore market share. Conversely, if reputations are far apart, a "market-sharing" effect dominates, whereby the CRA with lower reputation will inflate ratings in order to gain additional market share. Similarly, Frenkel (2015) finds that the degree to which competition can improve rating quality depends on how low the reputation of the entrant is relative to the incumbent. Finally, Manso (2013) explores the implications of competition in the presence of feedback effects from ratings to a firm's cost of capital. He finds that increased competition can result in downward pressure on ratings, which leads to a higher probability of default, and lower welfare.[8]

[6] See Bennett, Pierce, Snyder, and Toffel (2013) on auto emissions testing, and Lennox (2000), Chan, Lin, and Mo (2006), Lu (2006) and the review in DeFond and Zhang (2014) for audits.

[7] An issuer-paid CRA generates income from fees it collects from security issuers. In contrast, investor-paid CRAs generate income by charging individual and institutional investors for access to their ratings.

[8] In our setting, a "firm" is in fact a special purpose self-liquidating entity such that the survival of the

The empirical results of Griffin, Nickerson, and Tang (2013), Strobl and Xia (2012), and Jiang, Stanford and Xie (2012) support the existence of catering. Although they do not examine the effect of entry, Griffin, Nickerson, and Tang (2013) find that competition among CRAs leads to ratings inflation in the collateralized debt obligation (CDO) market. Strobl and Xia (2012) use the investor-paid CRA Egan-Jones to document that S&P's corporate ratings are more inflated in situations in which they face a greater conflict of interest as a result of their issuer-pays business model. Jiang, Stanford, and Xie (2012) find that S&P's transition from an investor-pay to an issuer-pay model resulted in higher ratings.

Give the unclear theoretical predictions, the effect of competition on ratings is an empirical question, but the empirical results to date are mixed. Becker and Milbourn (2011) and Cohen and Manuszak (2013) use data from prior to the financial crisis and find that increases in Fitch's market share are associated with more generous credit ratings. In contrast, Behr, Kisgen, and Taillard (2014) find that rating quality decreased after the SEC introduced a NRSRO certification process in 1975 that resulted in *less* room for competition. Bae, Kang, and Wang (2015) find that Fitch's entry did not affect the level of credit ratings. Doherty, Kartasheva, and Phillips (2012) find that when S&P entered the insurance rating market it actually applied *stricter* rating standards than the incumbent A.M. Best.[9] Xia (2014) shows that the entry of an investor-pays CRA improves the quality of ratings.

Even if competition does result in less stringent ratings, the mechanism behind this effect is still unclear. Much of the theoretical work (e.g., Skreta and Veldkamp 2009, Bolton, Freixas, and Shapiro 2012, and Sangiorgi and Spatt forthcoming) has focused on explicit rating "shopping," whereby issuers solicit ratings from multiple CRAs in search of the best ones. The presence of shopping does not necessarily indicate that CRAs are inflating ratings,

firm is less responsive to changes in credit ratings.

[9]Doherty, Kartasheva, and Phillips (2012) argue that this is likely due to the different incentives insurance companies have to seek additional ratings. A non-insurance corporate issuer usually seeks additional ratings in order to make its bonds appealing to investors with "regulatory constraints" (e.g., investors who can only hold bonds with ratings from two or more CRAs). An insurance company, in contrast, will seek an additional rating only if it allows it to charge a higher price to buyers of its policies such that seeking a more stringent rating is optimal.

though: they could be issuing ratings that are perfectly accurate given their private information, but cross-sectional differences in this private information could lead to differences in disclosed ratings. In contrast to shopping, rating catering is an action on the part of CRAs and occurs when they issue ratings that are higher than their private information dictates for the purpose of garnering more business. Unlike shopping, catering always implies some degree of rating inflation, and it is therefore a channel that is distinct from shopping.

2.3 Our Setting

The works closest in spirit to our paper, Becker and Milbourn (2011), Cohen and Manuszak (2013), and Bae, Kang, and Wang (2015), are set in time periods in which the incumbents' reputation in the particular asset class in question (corporate bonds in the case of Becker and Milbourn and Bae et al, and structured finance in the case of Cohen and Manuszak) was solid. Additionally, the benefit to inflating ratings was high due to the size of these markets during their time periods. In contrast, our setting is one in which competition has the best chance of leading to more *stringent* ratings for two reasons. First, our data come from a time period and asset class in which the incumbent rating agencies had very poor reputations. The massive downgrades of billions of dollars of RMBS and ABS CDOs and the failure of large financial institutions led to public backlash from lawmakers and lawsuits from investors. As our sample period begins in 2009, we have an environment in which competition is most likely to lead to more rigorous ratings as predicted in the model of Camanho, Deb, and Liu (2012).

Second, our setting is one in which the benefit from inflating was small. Theoretical work (e.g., Bar-Isaac and Shapiro 2013, Bolton, Freixas, and Shapiro 2012) shows that CRAs are least likely to inflate ratings when fee income from doing so is low. As the CMBS market has been relatively small post financial crisis, the benefits of issuing higher ratings to gain business are low relative to the benefits of exploiting a better reputation in the future. Along this dimension as well, therefore, our setup is one in which competition has the best chance of leading to more stringent ratings.

We also analyze how the entrants compete and show clearly that they do so by being more generous, which suggests catering. Given that there are far fewer issuers of structured finance products than corporate bonds, catering is likely to be a more important issue for this asset class. The magnitude of our point estimates regarding the effect of competition on incumbent ratings suggests that, indeed, competition may have even more deleterious effects in structured finance, and perhaps other similar asset classes, than in corporates. Finally, our setting is one in which shopping can and, as we show, does occur on a significant scale. Although the CMBS market itself is small relative to the corporate market, the set of all mortgage- and non-mortgage-related asset-backed securities (i.e., "structured finance") is larger by total issuance and by amount outstanding than the corporate market (SIFMA 2014b).

2.3.1 Hypotheses

Motivated by the theoretical literature and the unique aspects of our setting, we test the following hypotheses:

Hypothesis 1 *Entrant CRAs issue higher ratings than incumbents for the same security.*

After testing for differences in ratings between entrants and incumbents, we attempt to identify entrant catering by considering the following alternative hypotheses for these differences:

Hypothesis 1a *We observe higher entrant ratings because they rate securities that incumbents have have rated unexpectedly low.*

Hypothesis 1b *We observe higher entrant ratings because their rating models are less precise than those of incumbents.*

Hypothesis 1c *We observe higher entrant ratings because incumbents are excessively conservative as measured by average spreads on CMBS relative to similarly-rated securities in other asset classes.*

We then turn to the question of how entrant CRAs affect incumbent ratings. We first test whether the entrants affect incumbent ratings generally

Hypothesis 2 *The presence of the entrant CRAs affects incumbent ratings.*

We then attempt to identify the channel through which entry affects incumbent ratings

Hypothesis 2a *Entry affects incumbent ratings because it widens the scope for shopping.*

Hypothesis 2b *Entry affects incumbent ratings because incumbents increase catering to issuers in response to entry.*

3 Data and Variable Definitions

3.1 Data Collection and Sample Restrictions

We collect data from Bloomberg terminals on entrant and incumbent ratings, collateral characteristics, tranche structure, and coupons of CMBS issued from January 2009 through June 2014. We begin our sample in 2009 as the disruption in securitization markets resulted in very little issuance in 2008. Additionally, securities issued after the financial crisis are quite different from those issued before. We include all CMBS except ReREMIC deals, CDOs, or agency multi-family deals. Our incumbent CRAs are Moody's, S&P, Fitch, and Dominion Bond Rating Service (DBRS), and our entrants are Morningstar Credit Ratings LLC ("Entrant 1") and Kroll Bond Ratings ("Entrant 2"). All six CRAs are Nationally Recognized Statistical Rating Organizations (NRSROs).[10]

[10]See, for example, Beaver, Shakespeare, and Soliman (2006), Bongaerts, Cremers, and Goetzmann (2012), Cole and Cooley (2014), and Bruno, Cornaggia, and Cornaggia (forthcoming) regarding the importance of NRSRO certification for CRAs.

Entrant 1 was formed via the acquisition of a small investor-paid NRSRO by a large investment advisory services firm that subsequently converted the entity to an issuer-pays model. The conversion occurred after its acquisition in March 2010 (SEC 2012) and, because we are interested in studying issuer-paid ratings, we drop the small number of ratings (17 securities in total) by this entrant prior to its conversion. Entrant 1 also receives revenue from data services it provides to CMBS investors. Entrant 1 has plans to expand into the RMBS market and rated its first RMBS deal in late 2013 (Morningstar Credit Ratings, LLC 2013a). Entrant 1 provides corporate credit ratings as well but is not an NRSRO for corporate ratings.

Entrant 2's debut in the CMBS market was January 19th, 2011 (Kroll Bond Ratings 2011a). It adopted the tagline "[o]ur name is on the line" to underscore its "emphasis on ratings trust and accuracy" (Kroll Bond Ratings 2011a). Entrant 2 rated its first deal, a single borrower transaction, in July 2011 (Kroll Bond Ratings 2011b). It initially focused only on the large loan / single asset segment of the market, releasing its methodology for rating such deals on August 9th, 2011 (Kroll Bond Ratings 2011c). In 2012, it moved into the conduit/fusion market and issued methodology for rating such transactions on February 23, 2012 (Kroll Bond Ratings 2012). By mid-2013 entrant 2 had the third highest market share in CMBS ratings, and although initially active only in CMBS, it now also rates RMBS, credit card receivables securitizations, and auto loan securitizations. It has also recently started rating public finance bonds. However, its market share in these asset classes remains small.

3.2 Shopping

With the institutional detail described in Section 2.1 in mind, we define two measures of deal-level shopping. Both take advantage of the interdependence of securities in a deal and are based on missing ratings, as industry analysts have indicated that the presence of missing ratings in a deal indicates shopping (see, for example, Commercial Mortgage Alert 2014).

Table 1 provides an illustration of how we define the two measures. To define the first measure, *dealshop*1, we look for deals in which different tranches are missing ratings from different CRAs. For example, suppose we observe a deal with tranches A1, A2, and A3 (in order of seniority). Suppose S&P rates A2 and A3, Moody's rates A1 and A2, and entrant 2 rates all three tranches. Thus, two different tranches (A1 and A3) are missing ratings from different CRAs (S&P and Moody's). This implies the issuer had a desire for at least two ratings each on tranches A1 and A3, but that it *chose* to use different CRAs to rate them. In other words, the issuer shopped for ratings on A1 and A3. In this case, we code every security in the deal as $dealshop1 = 1$ with S&P and Moody's being the CRAs that were shopped. Our CRA-specific measures of shopping scale by the number of deals the CRA rates. That is, we define $dealshop2\_Y$ as the number of deals on which CRA Y gets shopped divided by the total number of deals in which CRA Y rates at least one security.

Our second measure, *dealshop*2, is less stringent than *dealshop*1 and takes a value of 1 for all securities in a deal for which a tranche in the deal is missing a rating from a CRA but a tranche below it in the capital structure has a rating from the same CRA. For example, if we observe that the A2 tranche does not have a rating from S&P but that the A3 tranche was rated by S&P, we would label every security in that deal as $dealshop2 = 1$. Such a rating pattern implies that S&P did analysis sufficient to assess the risk of loss, and thus rate, the A2 tranche, as it is not possible to rate the A3 tranche without first assessing the risk of eating through the capital above it. As such, we know there was a potential rating for the A2 tranche that was not purchased. To code *dealshop*2, we identify seniority based on the average rating on the tranche and then by its alphanumeric name, since for the majority of non-IOs, the priority of the tranche in the capital structure is indicated by its name (e.g., the A2 tranche is below the A1 tranche and the A3 tranche is below the B tranche). We sort first on average rating since the IO tranches are almost always labeled beginning with an 'X' but usually have high ratings. We do not label the deal as having been shopped if the missing rating is for an unrated tranche, or if the more senior tranche for which a rating is missing has less subordination than the less senior tranche. There are two advantages of *dealshop*1 over *dealshop*2. First, it prevents us from coding a deal as having been shopped simply because we observe fewer ratings for some tranches, and second, it requires no assumptions about the waterfall.

In addition to *dealshop*1 and *dealshop*2, we include the number of ratings, *nratings*, in some of our regressions. We include this variable because more observed ratings may indicate that an issuer went to more CRAs to inquire about rating the issue. For example, observing four ratings means the security was shopped to at least four CRAs, and possibly more, and that those four ratings were sufficiently high to induce the issuer to purchase them. An alternative view of shopping at the security level is offered in He, Qian, and Strahan (2016), who find that non-*AAA* RMBS securities with single ratings perform worse than those with multiple ratings. This is taken as evidence that single-rated tranches have been shopped *more* and thus many potentially low ratings, which would have indicated the observed poor performance, were never purchased. Hence, these results would suggest a measure of shopping should be decreasing in the number of ratings.

3.3 Summary Statistics

Table 2 summarizes the securities in our sample. Our sample contains 2,488 securities from 287 separate deals, and only rated securities are included. The variable *nratings* is the total number of ratings for that security. The average security is rated by at least 2 CRAs and some are rated by 4. Moody's and Fitch each rate more than half the securities, S&P rates a third, and DBRS rates just over a quarter. Entrant 1 rates only 379 securities, whereas Entrant 2 rates 1,006, more than S&P. In total, more than half of the securities issued are rated by at least one entrant.

The entrants generate ratings on an alphabetical scale comparable to the incumbents.[11] Hence, the ratings of all six CRAs in the sample can be mapped one-to-one to the same

[11]The entrants and incumbents use similar definitions to describe what various ratings for a structured finance security represent. The appendix contains the exact definitions for *AAA* securities; the definitions for lower ratings are analogous.

numerical scale. We map the alphabetic ratings to a 16 notch numerical scale as follows: $AAA = 16$, $AA+ = 15$, $AA = 14$, $AA- = 13$, $A+ = 12$, $A = 11$, $A- = 10$, $BBB+ = 9$, $BBB = 8$, $BBB- = 7$, $BB+ = 6$, $BB = 5$, $BB- = 4$, $B+ = 3$, $B = 2$, $B- = 1$. We drop all ratings below $B-$. Half of the securities are rated AAA by at least one CRA, and 46.9% are rated AAA by at least one incumbent, with the remaining 3.5% being rated AAA by only an entrant. The average rating assigned by incumbents is about one grade lower than the average rating assigned by the entrants. We discuss in the next section whether the differences in ratings across CRAs are because of differences in the securities they rate.

The size of the issue is the tranche size (*tranchesize*). We treat the small number of issues for which *tranchesize* is 0 or equal to the size of the deal (usually IO tranches) as missing for this variable. Subordination is the main measure of credit enhancement for non-IO structured finance products. It is the percentage of the value of all the securities in the deal that are below it in the priority of payments and the allocation of losses on the principal of the collateral to the principal of the tranches. Thus, AAA securities usually have the most subordination and $B-$ tranches usually have the least. Because IO securities have no principal balance, they have no subordination.

The main measure of expected maturity in the CMBS market is the weighted average life (WAL) which Bloomberg provides in years. The WAL is calculated by projecting the principal repayment schedule and then calculating the number of years from issuance in which the average dollar of principal is paid off. It is similar to Macaulay's duration but includes only anticipated principal payments rather than scheduled principal and interest payments. Because IO securities do not have a principal balance, they have no WAL. The WAL is calculated under particular assumptions about prepayment and default, and issuers usually provide a WAL in the prospectus supplement (Bloomberg populates its WAL field using these supplements). We use this measure to create categories of WAL: less than 3 years, 3 to 5 years, 5 to 7 years, and 7 years or more.

The securities in our sample vary in the form of the coupons they pay and in their expected maturity, and include (1) floating rate ("floaters"), which pay a constant fixed spread to one month LIBOR, (2) fixed rate, and (3) variable rate securities other than floaters.

Our data contains the shares of each property type backed by the loans in the pool for the top 3 most common property types in that pool. From the top 3 property type shares, we construct the shares of retail, office, hospitality, and industrial property. To account for geographic heterogeneity, we construct variables measuring the share of loans in each pool that were originated in five MSAs: New York-Newark-Jersey City (*nyshare*), Los Angeles-Long Beach-Anaheim (*lashare*), Houston-Woodlands-Sugar Land (*houshare*), Miami-Fort Lauderdale-West Palm Beach (*mishare*), and Chicago-Naperville-Elgin (*chishare*). These five cities are the largest by deal count.

We have three additional variables that describe the collateral, all of which are measured at origination of the loans: (1) the weighted average loan-to-value (*waltv*), the weighted average debt-service coverage ratio (*wadscr*), which is the ratio of the net rents (usually called net operating income (NOI)) the property is expected to earn divided by the required mortgage payment, and (3) the weighted average maturity (*wam*) of the loans backing the security.

The mean issuance date of a security is June 2012. The CMBS market recovered slowly from the financial crisis. Thus, issuance of CMBS increases gradually over the sample, with 28 securities issued in 2009, 112 in 2010, 343 in 2011, 550 in 2012, 1006 in 2013, and 449 in the first half of 2014.

To account for heterogeneity in CMBS issuers in some of our empirical analysis, we include the total amount of issuance for the issuer/sponsor (*sponsortot*) in the year the security is issued. We do so following the finding of He, Qian, and Strahan (2012) for the RMBS market that larger issuers often get more favorable ratings.

CMBS deals differ in their structure and the market is segmented according to the type, which is important because the CRAs have different methodologies for rating different types. Our first type is conduit/fusion, which comprise about two thirds of our sample. The second category is large loan or single loans, which are deals backed by only a few or one large loan. We combine the Bloomberg categories Single-Asset and Large Loans into *typlarge* since we have relatively few large loan deals that are not only one loan and CRAs usually use the same methodology for rating Single-Asset and Large Loan deals. Our *typlarge* category constitutes 27% of our sample. We group the remaining deals (portfolio, European, and Small Balance) into an "other" category that contains 5% of the securities in our sample.

Table 3 tabulates the frequency of *dealshop*1 and *dealshop*2 across various time periods and deal types. By our more stringent measure of shopping, *dealshop*1, 6% of deals in our sample are shopped, whereas nearly a quarter are shopped according to *dealshop*2. Shopping is higher post entry by both measures (column (3) vs column (2)) and, consistent with the prediction of Skreta and Veldkamp (2009), it is more common in more complex (and harder to rate) conduit/fusion deals than in large loan deals (column (4) vs. column (5)). Incumbents are about as likely as entrants to get shopped. It is thus not the case that issuers always purchase incumbent ratings and then shop for entrant ratings.

4 The Entrants' Ratings

Reflecting the belief that competition improves the quality of credit ratings, the SEC permitted both entrants to remain NRSROs, despite them deriving a large share of their CMBS rating revenue from a handful of issuers, because it was consistent with the SEC's goal of enhancing competition (SEC 2011, 2012, 2013). Figure 1 documents the evolution of the entrants' market share of the CMBS deal types. Entrant 1 does not exhibit much forward momentum, rating no securities in 2010 and around 20% in 2011 and 2013. Entrant 2 enters the market halfway through 2011 such that it rates just 10% of securities issued that year but 39% of large loan deals, consistent with its initial focus on that market segment. Through the first half of 2014, it rates 56% of CMBS, giving it the third largest market share in that six month period ahead of S&P.

Part of this is due to S&P losing market share as a result of a mishap on a July 2011 deal (it pulled ratings after pricing but before settlement) which led it to not rate any conduit deals for several months. S&P asserts its temporary exit from the conduit market was voluntary (Reuters, 2011), but some commentators in the financial press assert that it was effectively shut out (see, for example, Tempkin 2012a). Both entrants had plans to enter the CMBS market well in advance of this incident, though, so the entry is not endogenous to S&P's problems. In fact, entrant 2 initially entered only the large loan segment of the CMBS market; it could not have known it would have a unique opportunity in the conduit market due to S&P's problems.

4.1 Differences Between Entrant and Incumbent Ratings

We now turn to testing Hypothesis 1, that entrants rate higher than incumbents. Table 4 compares entrant and incumbent ratings for the set of securities rated by both, which allows us to hold security characteristics constant. The results of the paired t-tests indicate that both entrants issue systematically more generous ratings that the main incumbents on the same securities.

The differences between both entrants' ratings and those of S&P, Moody's, and Fitch are all positive and statistically significant at the 1% level, indicating that the entrants rate more generously. On average, entrant 1 rates one grade higher than the three main incumbents, but there is no significant difference between entrant 1's ratings and those of DBRS. Entrant 1 rates IO securities 3.1 grades higher than the average of the four incumbents, but rates non-IOs only 0.4 grades higher, although the difference is still highly statistically significant.

Entrant 2 is somewhat less generous than entrant 1, although on average it still rates a security 0.4 grades higher than incumbents. The differences between entrant 2's ratings and those of Fitch, Moody's, and S&P are positive and significant at the 1% level. DBRS rates slightly higher, on average, than entrant 2. Like entrant 1, entrant 2's higher ratings are much more pronounced for IO tranches: it rates those an average of 2.6 grades higher, but rates non-IOs only 0.04 grades higher. Entrant 2's higher ratings in non-IO tranches are also concentrated in the early part of the sample (2011-2012) when it is struggling to gain market share. In contrast, there is no statistical difference between entrant 2 and the average incumbent rating on non-IOs in the second half of the sample (2013-2014).

S&P is the most "conservative" incumbent relative to the entrants, which may be because it faced greater regulatory pressure. Regulators' concerns centered on a period in early 2011 during which S&P is alleged to have deviated from its own published standards in its conduit ratings without disclosing the deviations from those standards to investors. The regulatory pressure culminated in S&P agreeing to stop rating conduit deals for a period of one year beginning in January 2015 (Scully 2015). While we do not know for certain, as the matter was settled out of court, it seems possible that these regulatory concerns were related to the aforementioned July 2011 ratings mishap that led to S&P not rating any conduit transactions for several months thereafter.

The entrants' ratings of non-IOs are usually within four notches of the incumbents' average rating, a phenomenon illustrated in Figure 2 which plots the average incumbent rating against the rating of the entrant for each non-IO security rated by both. If entrant and incumbent ratings were the same, the dots would line up along the 45 degree line. Alternatively, if the differences between entrants and incumbents were simply a result of random differences of opinion, we would observe the dots in Figure 2 randomly scattered around the 45 degree line. Consistent with the statistics in Table 4, however, the entrants' ratings are usually above the 45 degree line. The difference in ratings is even more pronounced in the IO tranches—the entrants rate IOs *AAA* almost uniformly, and their average rating is nearly three notches higher than the average incumbent rating.

The uniformity in IO ratings by the entrants may suggest they expend less resources in creating detailed models to assess risk, instead preferring to have a blanket policy that does not consider the variation in IO structures in the CMBS market. They may do this because, as discussed in Section 2.1, IO investors use ratings less for their information content than for their certification benefit. By issuing nearly uniform AAA ratings to IOs, the entrants can simultaneously save on information production costs and meet or exceed the ratings-based certification threshold. Although this results in less informative ratings, the consequences (in terms of future loss of business from IO investors) are mitigated because IO investors are less sensitive to informative ratings as they are to ratings that meet their investment guidelines.

Selection, Incumbent Conservatism, or Catering?

We have shown that the difference between the entrants' and incumbents' ratings persists after controlling for security characteristics. While this suggests catering, it is possible that such differences arise due to selection effects or because the incumbents are excessively conservative. To determine whether this is the case, we look at three alternative hypotheses. First, we consider whether the differences arise because issuers purchase entrant ratings only after observing a low rating from one or more incumbents (Hypothesis 1a). Second, we examine whether the incumbents models are more precise than the entrants' in the sense of a larger fraction of the variance in ratings being explained by observable security characteristics (Hypothesis 1b). Third, we look at whether investors view incumbents' ratings as excessively conservative (Hypothesis 1c).

Selection due to low ratings from incumbents If the differences arise because issuers choose to buy entrant ratings only after observing an unexpectedly low rating from one or more incumbents, a gap would exist even if the entrants do not issue systematically higher ratings. In other words, the difference would not be due to catering on the part of entrants.

To test this, we estimate a model of predicted incumbent ratings and test whether an entrant is more likely to rate an issue if the incumbent rates low. That is, we first estimate

$$avgratingincumbent_{i,j,t} = \alpha_0 + \alpha_{\mathbf{x}}' Controls_{i,j,t} + \epsilon_{i,j,t} \tag{1}$$

where i indexes the security, j indicates the deal type, and t indicates the year of issuance. The controls include dummies for the year of issue, deal type dummies, collateral characteristics, dummies for the coupon type (fixed rate, floating rate, or variable rate), and the *ex ante* WAL of the security in categories.

We then generate predicted ratings for each security ($predictavgratingincumbent_{i,j,t}$) the incumbent rates and compute the "error" in average incumbent ratings:

$$avgincumerror_{i,j,t} = avgratingincumbent_{i,j,t} - predictavgratingincumbent_{i,j,t} \tag{2}$$

Additionally, we compute the binary variable

$$incumlow_{i,j,t} = \begin{cases} 1 & \text{if } avgratingincumbent_{i,j,t} < predictavgratingincumbent_{i,j,t} \\ 0 & \text{else.} \end{cases} \tag{3}$$

Finally, we estimate whether a low incumbent rating increases the probability of an entrant rating via

$$ratedentrant_{i,j,t} = \alpha_0 + \alpha_1 avgincumerror_{i,j,t} + YrofIssueFEs + DealTypeFEs + \epsilon_{i,j,t} \tag{4}$$

and

$$ratedentrant_{i,j,t} = \alpha_0 + \alpha_1 incumlow_{i,j,t} + YrofIssueFEs + DealTypeFEs + \epsilon_{i,j,t} \tag{5}$$

by probit. In equations (4) and (5), $YrofIssueFEs$ and $DealTypeFEs$ denote fixed effects for the year of issue and security type, respectively. The dependent variable, $ratedentrant$, takes a value of 1 if an entrant rates the security and 0 otherwise. We estimate equations (4) and (5) at the security level rather than the deal level as CRAs sometimes rate only a subset of securities in a deal rather than the entire deal.

The α_1 coefficients are statistically insignificant in all but one specification and change sign depending on the specification. The results are available in an appendix. We thus reject Hypothesis 1a.

Selection due to noisier entrant ratings Another reason we might *observe* systematically higher entrant ratings even if they do not *rate* systematically higher on purpose is if the entrants have noisier rating models. By noisier, we do not mean less accurate in the sense of being worse predictors of *ex post* default; as we discuss below, the nature of performance in structured finance makes it difficult to assess accuracy from an *ex post* perspective until many years after issuance. Rather, noise refers to lower precision in the sense of observables explaining less of the variation in ratings. If entrant ratings are higher variance, issuers may choose, in a tie breaker situation, to purchase an entrant rating only if it is greater than or equal to the incumbent rating. While this channel is not entirely distinct from catering, since it too implies that the entrants garner business by rating higher than the incumbents, it implies a less deliberate strategy on the part of the entrants than having a methodology geared toward systematically higher ratings.

To explore this possibility, we estimate separate rating models for each of the three main incumbents and the two entrants using our control variables and data from 2011 onward. The R^2s are similar across CRAs indicating that the entrants' ratings are similar in precision to those of the incumbents. We thus reject Hypothesis 1b. The results from these regressions are available in an appendix.

Are incumbent ratings excessively conservative? A final explanation for higher observed entrant ratings is that the incumbents are simply being too conservative, which may be plausible given their experience in the financial crisis. The ideal measure of incumbent conservatism is to use the cross-sectional performance of CMBS securities and/or collateral to assess relative rating accuracy. However, as summary statistics (available in an appendix) indicate, the CMBS in our sample have thus far performed too well (i.e., the collateral and securities have suffered very few delinquencies or principal/interest shortfalls) to assess conservatism in this way. The primary reason for this is because, unlike in other asset classes (e.g., corporate bonds, municipal bonds), performance takes a considerable amount of time to observe in structured finance. Partly, the securities usually have stated maturity dates much longer (typically 30 to 40 years from issuance) than when most investors expect to stop receiving cash flows. Thus, a technical default in the sense of a writedown of principal for securities that have a principal balance, need not happen until that maturity date. Furthermore, some have argued (see Coval, Jurek, and Stafford 2009) that structured finance securities necessarily involve defaults more clustered in time than those on other kinds of bonds. The pricing of the Markit CMBX Series 6 and Series 7 indices, which are based on the performance of securities issued in 2012 and 2013, has also remained close to 100, indicating little expectation of imminent default. Additionally, there have been few rating changes by incumbent CRAs. Despite good performance thus far, it is difficult to conclude that the securities are being rated too conservatively, especially given that subprime and Alt-A RMBS deals issued during the subprime boom also performed well until mid-2006.

A further limitation in the structured finance market is that a time series of yields on individual securities is unavailable for two reasons. First, reporting requirements for structured products are much less standardized than for corporate bonds – there is nothing equivalent to TRACE for these asset classes with the exception of TBA agency securities since May 2011. As such, the vast majority of CMBS do not have current yield or spread information available in Bloomberg. Bloomberg reports *modeled* prices for most securities on many dates subsequent to issuance but does not have transaction prices.[12] The second challenge for getting a time series of yields is more fundamental: the majority of these products never trade after issuance. Bessembinder, Maxwell, and Venkataraman (2013) report that only about 20% of structured products traded at all in the 21 month period from May 2011 to January 2013. While about half of corporate bonds also trade infrequently (see, for example,

[12] As of May 2011, the Financial Industry Regulatory Authority (FINRA) requires reporting of all MBS transactions. FINRA released the data from 2011 onward early to three groups of researchers; see Atanasov and Merrick (2013), Bessembinder, Maxwell, and Venkataraman (2013), and Hollifield, Neklyudov, and Spatt (2013).

Edwards, Harris, and Piwowar 2007), there are far more corporate bonds than CMBS.

Absent variation in security performance or time series data on yields, we can assess whether the non-IO securities that the incumbents rate below AAA are conservatively rated by comparing the yields *at issuance* of CMBS with those of corporate bonds. We use the initial coupon as a measure of the yield for CMBS.[13]

Spreads on CMBS that the incumbents rate below AAA are almost always higher than spreads on like-rated corporate bonds.[14] While some of the higher spread on CMBS is likely an illiquidity premium, it is unlikely that this premium is enough to explain the more than 100 basis point average difference. Thus, the market seems to perceive these securities as riskier than corporate bonds of a given rating. Furthermore, spreads on BBB-rated corporate bonds (those closest to the investment grade-high yield cutoff) are almost uniformly *lower* than spreads on AA-rated CMBS (far away from the cutoff). We are thus able to reject Hypothesis 1c for the securities that account for most of the sample.

The observed difference in IO ratings is also unlikely to be driven by incumbent conservatism. As Beaman and Pendergast (2013) discuss, even the IOs attached to AAA securities may be much riskier than a AAA rating would indicate. The same is true of IOs attached to non-AAA non-IOs or IOs not attached to a particular non-IO tranche. In fact, as Beaman and Pendergast (2013) illustrate, IOs receiving most of their cash flows from mezzanine investment-grade (above $BB+$ but below AAA) tranches have more stable cash flows than IOs promised their cash flows from the non-IO AAA portion of the capital structure. The reason is that, while CMBS have far more prepayment protection than RMBS, any prepayments not completely covered by defeasance clauses for the entire loan term accrue to the most senior tranches first, thus reducing the interest available to pay IOs. The incumbent

[13]An, Deng, and Gabriel (2011) and He, Qian, and Strahan (2012) make similar assumptions in their use of coupons as initial yields for structured finance. Although some junior securities may price below par according to industry participants, the bias this creates for us is to *understate* the yields earned on more junior securities.

[14]This is consistent with Merrill, Nadauld, and Strahan (2014), who find that yields on highly-rated structured finance securities held by insurance companies were higher than yields on like-rated corporate bonds.

CRAs formerly had a practice of rating IOs AAA when the IOs received priority in the waterfall commensurate to a linked non-IO AAA's payments (Beaman and Pendergast, 2013). However, the incumbents abandoned this practice in 2010 so that their ratings better reflect the true risks of investing in IOs (Beaman and Pendergast, 2013).

4.2 Are Entrant Ratings Substitutes for Incumbent Ratings?

The entrants' ratings do not appear to be perfect substitutes for the incumbents' ratings, as an issuer's choice to get an entrant rating appears to be closely related to opting for an additional rating. For the 2011-2014:Q2 time period, the mean number of ratings for securities that get rated by an entrant is 2.8, while it is 2.0 for securities that do not get rated by an entrant. The difference in the number of ratings that securities rated by an entrant have persists in a multivariate context. In a regression of the number of ratings on our full set of controls and *ratedentrant*, the coefficient on *ratedentrant* is 0.7 in the non-IO sample and 0.8 in the IO sample. It is statistically significant at the 1% level in both the non-IO and IO samples. In the interest of brevity, the results are available upon request.

5 The Effect of Entry on Incumbent Ratings

While the entrants give more generous ratings to gain business, it is unclear whether the incumbent CRAs would necessarily respond to competitive pressure, or how much more issuers are able to shop when there are more CRAs. First, the incumbents may value their reputations enough that they ignore the competitive pressure, especially because, for the time being, the entrants compete only in structured finance products. Second, it does not appear that entrant ratings are treated as perfect substitutes by issuers. Finally, it is unclear whether the market actually *believes* higher entrant ratings are accurate. As discussed in the appendix, there is weak evidence that investors require higher initial yields for securities rated AAA by an entrant vs securities with AAA ratings from only incumbents.

However, theoretical work suggests that competition can exacerbate rating catering. Additionally, this literature shows that incumbent ratings will certainly increase in response to competition via the shopping channel. Thus, to test Hypothesis 2, whether entry into the CRA market affects incumbents' ratings, we construct variables to separately identify both potential channels (Hypotheses 2a and 2b).

5.1 Regression Design

Our identification of the effect of competition on incumbent ratings exploits differences in the market share of the entrants over time and within subsegments of the CMBS market (large loan, conduit/fusion, or other). There is substantial variation in which types of CMBS the entrants are active in. Hence, for each year and CMBS type, we construct the entrants' market shares as the percent of securities they rate. We then include year and CMBS type fixed effects to control for variation in ratings over the business cycle and the fact that some CMBS types may be riskier than others. We also include a quadratic trend for the number of months since the start of the sample to control for trends in rating standards unrelated to the entrants.

We estimate

$$\begin{aligned} avgratingincumbent_{i,j,t} &= \alpha_0 + \alpha_1 entrant1share_{j,t} + \alpha_2 entrant2share_{j,t} \\ &\quad + \alpha_{\mathbf{x}}' Controls_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{6}$$

where the controls include dummies for the year of issue and deal type, collateral characteristics, dummies for the coupon type (fixed rate, floating rate, or variable rate), a quadratic in the months since the start of the sample, and the *ex ante* WAL of the security in categories.

The independent variables of interest are $entrant1share_{j,t}$ and $entrant2share_{j,t}$, which are the percentage of securities of type j issued in year t that are rated by entrants 1 and 2, respectively. Competition results in more generous ratings by the incumbents if $\alpha_1 > 0$ or

$\alpha_2 > 0$.

The specification implied by equation (6) assumes the effect each independent variable has on incumbent ratings is the same along all notches. This may not be true, however, as ratings are ordinal in nature. For example, the entrants' market share may have more of an effect on whether an incumbent rates a security *AA+* vs. *AAA* than on whether it rates a security *A+* vs. *AA−*. We thus estimate equation (6) using both OLS and an ordered probit. The latter preserves the ranking of the different ratings but does not impose a linearity assumption.

Subordination

Given the importance of the *AAA* tranches for issuers, we also examine whether the entrants altered the tranches that the incumbents rated *AAA*. In particular, we estimate

$$\begin{aligned} Subordination_{i,j,t}^{AAA} &= \beta_0 + \beta_1 entrant1share_{j,t} + \beta_2 entrant2share_{j,t} \\ &\quad + \beta_{\mathbf{x}}' Controls_{i,j,t} + \epsilon_{i,j,t} \end{aligned} \tag{7}$$

In estimating equation (7), we include only securities that one of the incumbent CRAs rates *AAA*. More competition among CRAs lowers the amount of subordination if $\beta_1 < 0$ or $\beta_2 < 0$.

5.2 Addressing selection issues

In Section 4.1 we discuss and try to rule out potential selection-based explanations for why we observe higher entrant ratings. There are also selection issues that must be accounted for when we test for the effect of entry on incumbent ratings. It may be the case that incumbent rating levels would have risen *absent* competition from entrants. If so, any observed effect of entry on incumbent ratings might merely be due to the correlation between entrant market share and some unobserved driver of incumbent rating levels. This type of selection can be due to several factors. First, entrants might be able to identify deal types for which the market is improving or likely to improve and hence for which rating levels are likely to improve. A second source of selection may arise if entrants are more able to increase their market share in segments characterized by more issuer shopping (and hence higher rating levels). We are not aware of any theoretical work suggesting a particular reason for an exogenous increase in the desire to shop in a particular deal type and year. While the desire to shop may increase over time, or may be higher in a particular deal type due to differences in the complexity of the deal, our regressions control for both the deal type and the year. We find it much less likely that shopping demand should vary at the deal type - year level for reasons unrelated to the degree of competition because there is no obvious mechanism that would drive that behavior.

Despite this, we try to account for both potential sources of selection by constructing a measure of predicted entrant market share that is correlated with observed market share but plausibly uncorrelated with the error term in equation 6. We do so by estimating a regression of whether an entrant rates a security based on two sources of exogenous variation that changed the likelihood of an entrant rating.

For the first source of exogenous variation, we take advantage of a change to the Department of Labor regulations concerning the Employee Retirement Income Security Act of 1974 (ERISA). For pension funds under its purview, ERISA constrains structured finance investment choices to securities that are rated by certain rating agencies. The entrants were added to the list of approved rating agencies, and hence their ratings became eligible to use in ERISA certification, in July 2013 (see Kroll Bond Ratings 2013 and Morningstar Credit Ratings, LLC 2013b). Certification eligibility should increase demand from pension funds for entrant ratings, and thus increase the likelihood that an entrant rates a security, *without* having any direct effect on how incumbents rate. We thus define a variable called *posterisa* that takes a value of 1 from July 2013 onward, and 0 otherwise.

Additionally, we take advantage of the fact that entrant 2 initially rated only large loan deals, a decision it made before observing incumbent ratings during its first several months of existence. It did not release a methodology for conduit/fusion deals until February 2012 and did not rate its first conduit/fusion deal until March 2012. We thus define a variable called *entrant2out* as equal to 1 for all securities in conduit/fusion deals issued from July 2011 (entrant 2's debut) to February 2012. We expect that *entrant2out* will have a positive effect on the probability that entrant 1 rates a security, since the two ratings are imperfect substitutes, but a negative effect on the probability that entrant 2 rates a security. The fact that entrant 2 initially chose to focus on the large loan market rather than the conduit/fusion market should have no effect on incumbent ratings other than through how it influences the entrants' market shares.

We thus estimate a probit model of

$$ratedentrant_{i,t} = \gamma_0 + \gamma_{erisa} posterisa + \gamma_{e2out} entrant2out + DealTypeFEs + \gamma_{\mathbf{x}}' X_{i,t} + \upsilon_{i,j,t} \quad (8)$$

where $X_{i,t}$ includes $month$, $monthsq$, $floater$, $variable$, IO, geographic characteristics, and property type shares. Note that, in estimating equation (8), we exclude characteristics that are commonly subject to negotiation between CRAs and issuers such as the level of subordination. Because negotiation over the level of subordination also affects the size of the tranche and the WAL, we treat these variables as potentially subject to endogeneity bias and exclude them from equation (8). Similarly, issuers and CRAs often negotiate over the LTV of the loans, particularly for large loan deals, such that we exclude *waltv*. The LTV of the loans in turn influences *wadscr* and could affect *wam* such that we exclude these variables as well. Finally, we do not include year fixed effects since our goal is to simulate deal type shares by year based solely on *posterisa* and *entrant2out*, predetermined security characteristics, and a time trend.

After estimating equation (8) separately for each entrant, we then generate predicted values for the probability that an entrant rates each security in the sample, $pratedentrant_{i,t}$. We then assign a value of 1 to this variable if the predicted probability is greater than or equal to 0.5, and 0 otherwise. Finally, to get predicted entrant market shares, we calculate the mean of $pratedentrant$ for each entrant by year and CMBS subtype. After constructing the predicted shares, $pentrant1share$ and $pentrant2share$, we then estimate equations (6) and (7) using these shares as explanatory variables rather than $entrant1share$ and $entrant2share$.

5.3 Catering vs. Shopping

In our setting, the results from estimating equations (6) and (7) cannot distinguish between whether any change in the incumbents' ratings is due to catering or shopping. As discussed previously, theory suggests that competition is likely to lead to more catering and hence higher ratings, and the results of Section 4 indicate catering on the part of the entrants. Theory also suggests competition should lead to more shopping, thus both channels may be at work.

To understand the extent to which shopping drives the increase in incumbent ratings, we augment equations (6) and (7) with $ntranches$ and $dealshop1$ or $dealshop2$. If either coefficient is positive, some of the decrease in the stringency in ratings could be due to the greater capacity of issuers to shop for ratings, thus supporting Hypothesis 2a. On the other hand, if the coefficient on $entrant1share$ or $entrant2share$ is statistically significant and positive after controlling for the amount of deal-level shopping and the number of ratings, the data would suggest that incumbents cater to issuers more as entrants increase their market share (Hypothesis 2b).

5.4 Results

5.4.1 Average incumbent ratings

Table 5 presents the results from estimating equation (6) on the non-IO securities. In all specifications, we cluster the standard errors by year-deal type because our main variable of interest varies only at the year-deal type level. Columns (1) shows the effect of entrant market shares on the average incumbent rating. The coefficient on entrant 2's share is statistically significant at the 1% level while the coefficient on entrant 1's share is statistically significant at the 10% level. Column (4) presents the results when estimating the effect using the predicted entrant market shares rather than the actual ones; the results from the first stage of the estimation are in an appendix available from the authors. When the effect is estimated via the predicted entrant market shares rather than OLS, the coefficient on entrant 2's share continues to be statistically significant at the 5% level. The coefficient on $entrant1share$ is positive but is no longer statistically significant.

The economic magnitude of the effect for non-IO tranches is such that a 10 percentage point increase in Entrant 2's market share raises the average incumbents' rating by roughly 0.35 grades. As Entrant 2 increased its overall market share from 0 to 56% (see Table A.2), the effect is economically important since it implies an increase in average ratings by incumbents of more than a grade. The magnitude of the coefficient on Entrant 1's share is slightly higher and implies that a 10 percentage point increase in market share results in a 0.4 grade higher average incumbent rating.

One possible reason that we observe positive coefficients on the entrant market shares that is not due to catering is positive learning on the part of incumbents. In particular, it is possible that changes to Moody's and S&P's methodologies for some CMBS securities are the result of learning from the entrants' methodologies. If the model changes by the incumbents are because they see the entrant methodologies, decide they are more accurate, and then make changes accordingly, the positive coefficients could indicate something other than catering. The two relevant changes to incumbent ratings are a February 2012 change in Moody's IO rating methodology (Moody's Investors Service 2012) and a September 2012 change in S&P's Conduit/Fusion and Large Loan methodology (Tempkin 2012b). Entrant 2 released its large loan deal methodology in Aug 2011 and its conduit/fusion Feb 2012. Entrant 1 released a general methodology in June 2012.

To test for this possibility, we estimate the effect of $entrant1share$ and $entrant2share$ for each of the three main incumbents separately. Because Fitch had no changes to its methodology post-entry and Moody's had no substantive changes to its rating of non-IO tranches, if positive learning is the only reason we observe higher incumbent ratings in response to changes in the entrants' market share, we should observe positive coefficients only for S&P for the non-IO tranches. However, for each of the incumbents, $entrant2share$ is statistically significant at the 10% level. It is higher for Moody's and Fitch than for S&P. Entrant 1's share is statistically significant at the 5% level for S&P and Fitch but not for Moody's.

In summary, the results support Hypothesis 2 that the presence of the entrants affects incumbent ratings. The coefficients are lower for entrant 2 than for entrant 1. The finding of a stronger incumbent response to entrant 1 is consistent with the theoretical predictions of Frenkel (2015) to the extent that entrant 2 has a better reputation than entrant 1. Frenkel's analysis shows that incumbents will inflate ratings less in response to entry to the extent that the entrant has a better reputation (see Proposition 6ii). Entrant 1 rates systematically higher than entrant 2 on same issues (see Table 4) suggesting that entrant 1 may be the less credible of the two *ex ante*.

5.4.2 Subordination for securities rated AAA by an incumbent

Table 6 contains the results from estimating equation (7). Column (1) shows that, for tranches that at least one incumbent has rated AAA, a higher market share for Entrant 2 is associated with less subordination. A 10 percentage point increase in the market share of Entrant 2 lowers subordination by 1 percentage point, and this is statistically significant at the 1% level when we estimate the model by OLS. When we estimate the model using predicted market shares (Column (4)), $entrant2share$ is statistically significant at the 5% level and the magnitude is such that a 10 percentage point increase in market share is associated with a 0.7 percentage point decrease in subordination. Entrant 1's share is not statistically significant in either estimation. These results provide further support in favor of Hypothesis 2 sample but, similarly to our results for the level of ratings, the evidence is stronger for entrant 2 than for entrant 1.

5.4.3 Shopping

Table 5 compares our benchmark incumbent rating results with the results when we include our deal-level shopping measure and the total number of ratings the security receives. The coefficients on the entrant shares decrease in magnitude when moving from columns (1) and (4) to (2) and (5) in Table 5 and the coefficients on both $nratings$ and $dealshop1$ are positive and statistically significant at the 5% level. When we use $dealshop2$ as the measure of shopping (columns (3) and (6)), its coefficient is statistically insignificant, but $nratings$ is still positive and significant, and the coefficients on the entrant shares decrease by a similar magnitude when moving from columns (1) and (4) to (3) and (6). The results in Table 5 indicate that some of the increase in incumbent ratings is due to shopping on the part of issuers, but a substantial portion appears to be explained by catering on the part of incumbents.

There is less evidence that shopping affects the subordination of the AAA tranches, however. In Table 6, the coefficients on $entrant1share$ and $entrant2share$ change little when we add the shopping measure to the model and only $dealshop1$ is statistically significant (at the 10%) level. The results are similar in unreported robustness checks in which we regress subordination for other rating buckets (e.g., AA, A, BBB) on the number of ratings. Thus, the evidence suggests that both catering and shopping are likely responsible for the observed increase in average incumbent ratings in the non-IO sample, corroborating Hypotheses 2b and 2a.

We also estimate the effect of entrant market shares on the level of incumbent ratings in the IO sample. The results are available in Table 7. In the IO sample, incumbent ratings are increasing in entrant 2's market share but not in entrant 1's market share when we do not include our shopping variables. When we include the shopping variables, however, neither entrants' market share is statistically significant but both $dealshop1$ and $nratings$ are significant at the 5% level. Thus, issuer shopping explains all of the observed increase in incumbent ratings, corroborating only hypothesis 2a.

What explains the lack of incumbent response in IOs despite the nearly uniform AAA entrant ratings? As previously discussed, a substantial portion of the investor base for IOs is informed investors that want ratings solely for certification purposes. The nearly uniform AAA ratings of entrants indicates that there is little information content in those ratings. As such, the investors that are happy with an entrant rating simply want a higher rating regardless of its accuracy. The IO ratings of incumbent CRAs, on the other hand, likely have some information content. To compete with the entrants' ratings on IOs for certification-motivated investors, the incumbents would have to revise their IO ratings so dramatically that it may risk making it obvious they are responding to the entrants' threat rather than changing their views of the risk of these securities. That would cost the incumbents reputational capital and their base of IO investors that do care about the information content of ratings. Of course, the incumbents could perhaps credibly revise their ratings upwards by a notch once they observe entrant ratings. But even that would be insufficient to induce investors who solely care about certification to purchase their ratings over an entrant's, given that the gap would still be two notches or more. Thus, the incumbent CRAs do not respond at all since doing so would provide no benefit in terms of increased fee income, while at the same time risking reputational capital.

6 Conclusions

We have studied the effect of CRA entry on the level of ratings in structured finance. The entrants issue systematically higher ratings than the incumbents, and this indicates a strategy of catering to issuers. Furthermore, as the entrants' market share increases, the incumbents' ratings rise and the level of subordination they require for AAA tranches falls. The effect of entrant share on incumbent ratings is robust to the use of predicted market shares rather than actual market shares showing that the effect is unlikely to be purely due to selection—rather, incumbents appear to respond to entry. The observed increase in the ratings of the incumbents is due to both rating catering on their part and to shopping by issuers.

A limitation of our analysis is that we are unable to offer any theory, nor empirical support for existing theories, regarding which particular securities the incumbents rate. While we have addressed several specific concerns regarding reverse causality, we cannot foreclose the possibility that some of our results are due to selection. We hope future research can provide greater insights into why we see entrants rate some securities but not others.

Furthermore, it is too soon to assess the relative accuracy of the ratings of the incumbents and entrants in our market given the nature of default in structured finance. We cannot be certain that the entrants' higher ratings will not be justified based on *ex post* losses. The theoretical literature identifies an *upward* bias from competition, however, so it is less probable that the incumbents are excessively conservative in their ratings. Alp (2013) has also shown that, historically, moves towards relaxing rating standards have been associated with more default such that relaxation of standards has been associated with less accurate ratings. Finally, the theoretical literature indicates that the shopping that we uncover is not welfare improving. As such, our results suggest that, contrary to the stated belief of the SEC and the policy of European regulators, increasing competition among CRAs is likely to exacerbate, rather than reduce, any tendency the CRAs have to issue inflated ratings unless both the rating shopping and catering problems are addressed.

References

Adelino, Manuel and Miguel A. Ferreira, forthcoming. Bank Ratings and Lending Supply: Evidence from Sovereign Downgrades. Review of Financial Studies.

Almeida, Heitor, Igor Cunha, Miguel A. Ferreira, and Felipe Restrepo, forthcoming. The Real Effects of Credit Ratings: The Sovereign Ceiling Channel. Journal of Finance.

Alp, Aysun, 2013. Structural Shifts in Credit Rating Standards. Journal of Finance, 63:6, 2435-70.

An, Xudong, Yongheng Deng, and Stuart Gabriel, 2011. Asymmetric Information, Adverse Selection, and the Pricing of CMBS. Journal of Financial Economics, 100, 304-25.

Ashcraft, Adam, Goldsmith-Pinkham, Paul and James Vickery, 2010. MBS Ratings and the Mortgage Credit Boom. FRB of New York Staff Report No. 449.

Atanasov, Vladimir and John J. Merrick Jr., 2013. The Effects of Market Frictions on Asset Prices: Evidence from Agency MBS. Manuscript, College of William and Mary.

Bae, Kee-Hong, Jun-Koo Kang, and Jin Wang, 2015. Does Increased Competition Affect Credit Ratings? A Reexamination of the Effect of Fitch's Market Share on Credit Ratings in the Corporate Bond Market. Journal of Financial and Quantitative Analysis, 50:5, 1011-35.

Baghai, Ramin P., Henri Servaes, and Ane Tamayo, 2014. Have Rating Agencies Become More Conservative? Implications for Capital Structure and Debt Pricing. Journal of Finance, 69:5, 1961-2005.

Bar-Isaac, Heski and Joel Shapiro, 2013. Ratings Quality Over the Business Cycle. Journal of Financial Economics, 108, 62-78.

Beaman, John and Lisa Pendergast, 2013. Investing in CMBS IO. Ch. 5.3 in CRE Finance Council: CMBS E-Primer.

Beaver, William H., Catherine Shakespeare and Mark T. Soliman, 2006. Differential Properties in the Ratings of Certified versus Non-certified Bond-rating Agencies. Journal of Accounting and Economics, 42, 303-34.

Becker, Bo and Todd Milbourn, 2011. How did Increased Competition Affect Credit Ratings? Journal of Financial Economics, 101, 493-514.

Behr, P., Kisgen, D. and J. Taillard, 2014. Did Government Regulations Lower Credit Rating Quality? Working paper,
SSRN $http://papers.ssrn.com/sol3/papers.cfm?abstract_id = 2412294$

Bennett, Victor Manuel, Lamar Pierce, Jason A. Snyder, and Michael W. Toffel, 2013. Customer-Driven Misconduct: How Competition Corrupts Business Practices. Management Science, 59:8, 1725-42.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2013. Introducing Daylight to Structured Credit Products. Financial Analysts Journal, 69:6, 55-67.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro, 2012. The Credit Ratings Game. Journal of Finance, 67:1, 85-111.

Bongaerts, Dion, K.J. Martijn Cremers, and William N. Goetzmann, 2012. Tiebreaker: Certification and Multiple Credit Ratings. Journal of Finance, 67:1, 113-52.

Boot, Arnoud W.A. and Anjan V. Thakor, 1993. Security Design. Journal of Finance, 48:4, 1349-78.

Bruno, Valentina, Jess Cornaggia, and Kimberly J. Cornaggia, forthcoming. Does Certification Affect the Information Content of Credit Ratings? Management Science.

Camanho, Nelson, Pragyan Deb, and Zijun Liu, 2012. Credit Rating and Competition. Working paper, Católica Lisbon School of Business & Economics.

Chan, K. Hung, Kenny Z. Lin, and Phylli Lai-lan Mo, 2006. A Political-economic Analysis of Auditor Reporting and Auditor Switches. Review of Accounting Studies, 11, 21-48.

Cohen, Andrew and Mark D. Manuszak, 2013. Ratings Competition in the CMBS Market. Journal of Money, Credit and Banking, 45:1, 93-119.

Cole, Harold and Thomas F. Cooley, 2014. Rating Agencies. NBER Working Paper 19972.

Commercial Mortgage Alert, 2014. Issuers Test Split Ratings on Senior CMBS. September 19.

Cornaggia, Jess, Kimberly J. Cornaggia, and Ryan Israelson, 2014. Credit Ratings and the Cost of Municipal Financing. Working Paper, Indiana University.

Coval, Joshua D., Jakub W. Jurek, and Erik Stafford, 2009. Economic Catastrophe Bonds. American Economic Review, 99:3, 628-66.

DeFond, Mark, and Jieying Zhang, 2014. A Review of Archival Auditing Research. Journal of Accounting and Economics, 58, 275-326.

Dierker, Martin, Daniel Quan, and Walter Torous, 2005. Valuing the Defeasance Option in Securitized Commercial Mortgages. Real Estate Economics, 33:4, 663-80.

Doherty, Neil A., Anastasia V. Kartasheva, and Richard D. Phillips, 2012. Information Effect of Entry into Credit Ratings Market: The Case of Insurers' Ratings. Journal of Financial Economics, 106, 308-30.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007. Corporate Bond Market Transaction Costs and Transparency. Journal of Finance, 62:3, 1421-51.

Frenkel, Sivan, 2015. Repeated Interaction and Rating Inflation: A Model of Double Reputation. American Economic Journal: Microeconomics, 7:1, 250-80.

Fulghieri, Paolo, Günter Strobl, and Han Xia, 2014. The Economics of Solicited and Unsolicited Credit Ratings. Review of Financial Studies, 27:2, 484-518.

Griffin, John M., Jordan Nickerson, and Dragon Yongjun Tang, 2013. Rating Shopping or Catering? An Examination of the Response to Competitive Pressure for CDO Credit Ratings. Review of Financial Studies, 26:9, 2270-310.

Griffin, John M. and Dragon Tang, 2012. Did Subjectivity Play a Role in CDO Credit

Ratings? Journal of Finance, 67:4, 1293-328.

He, Jie (Jack), Jun ‘QJ’ Qian, and Philip E. Strahan, 2012. Are All Ratings Created Equal? The Impact of Issuer Size on the Pricing of Mortgage-Backed Securities. Journal of Finance, 67:6, 2097-137.

He, Jie (Jack), Jun ‘QJ’ Qian, and Philip E. Strahan, 2016. Does the Market Understand Rating Shopping? Predicting MBS Losses with Initial Yields. Review of Financial Studies, 29:2, 457-85.

Hollifield, Burton, Artem Neklyudov, and Chester Spatt, 2013. Bid-Ask Spreads and the Pricing of Securitizations: 144a vs. Registered Securitizations. Manuscript, Carnegie Mellon University.

Jiang, John (Xuefeng), Mary Harris Stanford, and Yuan Xie, 2012. Does it Matter Who Pays for Bond Ratings? Historical Evidence. Journal of Financial Economics, 105, 607-21.

Kanter, James, 2012. Finance Ministers Clear Way for Credit Rating Competition in Europe. New York Times, March 31.

Kroll Bond Ratings, 2011a. Kroll Bond Ratings Makes Official Debut With Multi-Media Marketing Campaign. Press Release, Kroll Bond Ratings, January 19, 2011.

Kroll Bond Ratings, 2011b. KBRA Assigns Final Ratings to BAMLL Trust 2011-FSHN. Press Release, Kroll Bond Ratings, July 14, 2011.

Kroll Bond Ratings, 2011c. Kroll Bond Rating Agency Issues CMBS Single Borrower &

Large Loan Methodology. Press Release, Kroll Bond Ratings, August 9, 2011.

Kroll Bond Ratings, 2012. U.S. CMBS Multi-Borrower Rating Methodology. Manuscript, Kroll Bond Ratings, February 23, 2012.

Kroll Bond Ratings, 2013. Kroll Bond Rating Agency Now ERISA Eligible Following DOL Amendment. July 11, 2013.

Lennox, Clive, 2000. Do Companies Successfully Engage in Opinion Shopping? Evidence from the UK. Journal of Accounting and Economics, 29, 321-27.

Lu, Tong, 2006. Does Opinion Shopping Impair Auditor Independence and Audit Quality? Journal of Accounting Research, 44:3, 561-83.

Manso, G., 2013. Feedback Effects of Credit Ratings. Journal of Financial Economics, 109, 535-548.

Mathis, J., J. McAndrews and J.-C. Rochet, 2009. Rating the Raters: Are Reputation Concerns Powerful Enough to Discipline Rating Agencies? Journal of Monetary Economics, 56, 657-74.

Merrill, C. B., Nadauld T. D., and P. E. Strahan, 2014. Final Demand for Structured Finance Securities. Working paper,
SSRN $http://papers.ssrn.com/sol3/papers.cfm?abstract_id = 2380859$

Moody's Investors Service, 2012. Moody's Approach to Rating Structured Finance Interest-Only Securities.

Morningstar Credit Ratings, LLC, 2013a. Final Ratings Confirmation - Invitation Homes 2013-SFR1.

Morningstar Credit Ratings, LLC, 2013b. News Release: Morningstar Credit Ratings Now Qualifies as a Rating Agency Under Amended Underwriter Exemption of the Employee Retirement Income Security Act of 1974. July 10, 2013.

Reuters, 2011. S&P: U.S. CMBS Conduit/Fusion Pool Criteria Change. July 27. Available at
$http://www.reuters.com/article/2011/07/27/markets-ratings-uscmbs-idUSL3E7IR5E820110727$
(last accessed May 19, 2015).

Sangiorgi, Francesco and Chester Spatt, forthcoming. Opacity, Credit Rating Shopping and Bias. Management Science.

Scully, Matt, 2015. Ratings Shopping Run Amok in U.S. Property Debt Fuels Buyer Ire. Bloomberg, Apr. 15. Available at
http://www.bloomberg.com/news/articles/2015-04-15/ratings-shopping-run-amok-in-u-s-property-debt-fuels-buyer-ire
(last accessed May 19, 2015).

SEC, 2011. Release No. 34-65339, September 14, 2011.

SEC, 2012. Release No. 34-66514, March 5, 2012.

SEC, 2013. Annual Report on Nationally Recognized Statistical Rating Organizations as Required by Section 6 of the Credit Rating Agency Reform Act of 2006.

SIFMA, 2014a. U.S. Average Trading Volume.

SIFMA, 2014b. US Bond Market Issuance and Outstanding.

Skreta, V. and L. Veldkamp, 2009. Ratings Shopping and Asset Complexity: A Theory of Ratings Inflation. Journal of Monetary Economics, 56, 678-95.

Strobl, Günter and Han Xia, 2012. The Issuer-Pays Rating Model and Ratings Inflation: Evidence from Corporate Credit Ratings. Working paper, University of Texas (Dallas).

Tempkin, Adam 2012a. ABS - S&P Re-enters CMBS Ratings Game after Industry Shutout. Chicago Tribune, May 15.

Tempkin, Adam, 2012b. S&P Criticized Over Changes to CMBS Ratings Standards. CNBC, Oct. 12. Available at http://www.cnbc.com/id/100140849 (last accessed August 19, 2014).

Titman, Sheridan and Sergey Tsyplakov, 2010. Originator Performance, CMBS Structures, and the Risk of Commercial Mortgages. Review of Financial Studies, 23:9, 3558-94.

Xia, Han, 2014. Can Investor-Paid Credit Rating Agencies Improve the Information Quality of Issuer-Paid Rating Agencies? Journal of Financial Economics, 111, 450-68.

Table 1: Illustration of Rating Shopping Measures with Hypothetical Deals

Deal ABC

Tranche	A1	A2	A3
Subordination	20%	18%	16%
S&P Rating		AA-	A
Moody's Rating	AAA	AA-	
Entrant 2 Rating	AAA	AA	A
dealshop1	1	1	1
dealshop1_sp	1	1	1
dealshop1_moodys	1	1	1
dealshop1_entrant2	0	0	0
dealshop2	1	1	1
dealshop2_sp	1	1	1
dealshop2_moodys	0	0	0
dealshop2_entrant2	0	0	0

Deal DFG

Tranche	A1	A2	A3
Subordination	20%	18%	16%
S&P Rating	AA+		A
Moody's Rating	AAA		A-
Entrant 2 Rating	AAA	AA	A
dealshop1	0	0	0
dealshop1_sp	0	0	0
dealshop1_moodys	0	0	0
dealshop1_entrant2	0	0	0
dealshop2	1	1	1
dealshop2_sp	1	1	1
dealshop2_moodys	1	1	1
dealshop2_entrant2	0	0	0

Table 2: Summary Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
nratings	2488	2.4	2	0.7	1	4
numericsp	841	11.6	13	4.4	1	16
numericmoodys	1618	12.6	16	4.4	1	16
numericfitch	1442	12.0	14	4.7	1	16
numericdbrs	652	12.9	16	4.3	1	16
avgratingincumbent	2488	11.9	14	4.6	1	16
numericentrant1	379	12.8	16	4.1	1	16
numericentrant2	1006	12.7	16	4.4	1	16
avgratingentrant	1291	12.7	16	4.4	1	16
AAAanyone	2488	0.503	1	0.5	0	1
AAAincumbent	2488	0.469	0	0.499	0	1
AAAentrantonly	2488	0.035	0	0.183	0	1
cpnspread	2031	1.915	1.727	0.991	0.005	8.924
tranchesize	2438	165	75	253	1	4100
subordination	1854	19.6	18.5	13.2	0	75
IO	2488	0.2	0	0.4	0	1
floater	2488	0.13	0	0.34	0	1
variable	2488	0.47	0	0.5	0	1
walunder3	2052	0.13	0	0.34	0	1
wal3to5	2052	0.15	0	0.36	0	1
wal5to7	2052	0.07	0	0.26	0	1
walover7	2052	0.64	1	0.48	0	1
retailshare	2348	32	28	27	0	100
officeshare	2348	20	17	21	0	100
hospshare	2348	15	0	31	0	100
indshare	2348	1	0	4	0	28
waltv	2354	60	63	8	8	113
wadscr	2267	2.2	1.9	0.9	1.2	7.4
wam	2419	96.2	108	35.1	12	540
year	2488	2012.5	2013	1.1	2009	2014
sponsortot	2488	14809.4	13271.3	10259.6	14	34458
typconduitfusion	2488	0.68	1	0.47	0	1
typlarge	2488	0.27	0	0.44	0	1
typother	2488	0.05	0	0.22	0	1
nyshare	2178	16.3	10	24.7	0	100
lashare	2178	4.7	0	12.8	0	100
chishare	2178	2.9	0	9.1	0	100
mishare	2178	2.4	0	11.2	0	100
houshare	2178	1.5	0	4	0	26
dealshop1	2488	0.08		0.27	0	1
dealshop2	2488	0.35		0.48	0	1

Variable definitions in Table 2 are as follows: $nratings$ is the total number of ratings the security received; $numericsp$, $numericmoodys$, $numericfitch$, $numericdbrs$, $numericentrant1$, and $numericentrant2$ are the numeric ratings of S&P, Moody's, Fitch, DBRS, Entrant 1, and Entrant 2 where 16 corresponds to AAA and a rating of 1 corresponds to B-. $avgratingincumbent$ is the average rating assigned by the four incumbent CRAs. $avgratingentrant$ is the average rating assigned by the entrants. $AAAanyone$ takes a value of 1 if any CRA assigns the security a AAA rating and 0 otherwise. $AAAincumbent$ takes a value of 1 if any incumbent CRA assigns a AAA rating. $AAAentrantonly$ takes a value of 1 if only an entrant CRA assigns a AAA rating. $tranchesize$ is the \$ value of the issue (in millions). $cpnspread$ is the annual spread at issuance (in %) that the security pays relative to a US treasury of comparable maturity (available only for non-IO tranches). $subordination$ is the level of subordination (in %) of the security. IO takes a value of 1 if the security is an interest-only tranche. $floater$ takes a value of 1 if the coupon is a fixed spread above a benchmark index (almost always 1-month LIBOR). $variable$ takes a value of 1 if the coupon is variable rate other than a floater. $walunder3$, $wal3to5$, $wal5to7$, $walover7$ are indicator variables that take a value of 1 if the security's weighted average life (WAL) is in the range indicated. $retailshare$, $officeshare$, $hospshare$, and $indshare$ capture the percentage of the loans backed by retail, office, hospitality, and industrial properties. $waltv$ is the weighted average loan-to-value (LTV) of the loans (in %). $wadscr$ is the weighted average debt service coverage ratio. wam is the weighted average maturity of the loans measured in months. $year$ is the year of issuance of the security. $sponsortot$ is the total \$ volume (in millions) of CMBS issued by the lead sponsor of the deal in the year the security is issued. $typconduitfusion$, $typlarge$, and $typother$ are indicator variables for CMBS deal types. $nyshare$, $lashare$, $chishare$, $mishare$, and $houshare$ capture the percentage of the loans originated on property in the New York, Los Angeles, Chicago, Miami, and Houston MSAs, respectively. $dealshop1$ takes a value of 1 if the security is part of a deal in which alternate tranche ratings are missing from two different CRAs. $dealshop2$ takes a value of 1 if the security is part of a deal with a capital structure in which tranche n has a rating from CRA A, but tranche $n-1$ is *not* rated by CRA A.

Table 3: Frequency of Deals with Shopping

	(1)	(2)	(3)	(4)	(5)
Period	2009-2014:H1	2009-2010	2011-2014:H1	2009-2014:H1	2009-2014:H1
Deal Type	All	All	All	Conduit/Fusion	Large Loan
dealshop1	5.6%	0.0%	6.3%	9.8%	2.8%
dealshop1_sp	2.6%	0.0%	3.0%	7.4%	1.4%
dealshop1_moodys	6.1%	0.0%	6.6%	9.0%	2.0%
dealshop1_fitch	7.9%	0.0%	9.0%	10.9%	4.7%
dealshop1_dbrs	1.3%	0.0%	1.4%	2.4%	0.0%
dealshop1_entrant1	4.3%	-	4.3%	14.3%	0.0%
dealshop1_entrant2	5.3%	-	5.3%	5.0%	6.5%
dealshop2	24.4%	12.5%	25.9%	40.6%	13.8%
dealshop2_sp	2.6%	0.0%	3.0%	3.7%	2.8%
dealshop2_moodys	8.8%	0.0%	9.6%	7.2%	16.3%
dealshop2_fitch	23.8%	22.2%	24.1%	35.9%	7.0%
dealshop2_dbrs	0.0%	0.0%	0.0%	0.0%	0.0%
dealshop2_entrant1	14.9%	-	14.9%	35.7%	3.2%
dealshop2_entrant2	18.9%	-	18.9%	28.3%	3.2%

Notes: 1) Data includes all CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 2) Statistics are deal-level. 3) See Table 2 for variable definitions. 4) Our CRA-specific measures of shopping scale by the number of deals the CRA rates. That is, we define $dealshop2\_Y$ as the number of deals on which CRA Y gets shopped divided by the total number of deals in which CRA Y rates at least one security.

Table 4: Comparison of Entrants' Ratings with Incumbents' on Same Issues

Entrant Rating	S&P	Moody's	Fitch	DBRS	Incum. Avg.	Difference	N	T-stat
Panel A: Entrant 1 vs. Incumbents								
12.36	11.11					1.25***	195	6.0
13.38		12.51				0.87***	177	5.3
13.16			12.52			0.64***	151	4.8
13.92				13.95		-0.03	39	-0.2
12.80					11.82	0.98***	379	8.1
IOs only:								
16.00					12.86	3.14***	75	6.7
non-IOs only:								
12.01					11.57	0.44***	304	6.7
non-IOs only, 2011-2012:								
12.06					11.74	0.32***	119	3.2
non-IOs only, 2013-2014:								
11.97					11.45	0.52***	185	6.0
Panel B: Entrant 2 vs. Incumbents								
12.48	11.81					0.67***	296	4.5
13.55		13.27				0.28***	674	4.9
12.63			12.28			0.35***	574	6.2
13.39				13.46		-0.07**	216	-2.3
12.69					12.27	0.42***	1006	7.4
IOs only:								
15.77					13.14	2.63***	149	8.3
non-IOs only:								
12.16					12.12	0.04**	857	2.2
non-IOs only, 2011-2012:								
11.81					11.71	0.10***	214	3.2
non-IOs only, 2013-2014:								
12.27					12.25	0.02	643	0.9
Panel C: Entrant Average vs. Incumbents								
12.37	11.45					0.92***	443	7.0
13.52		13.11				0.41***	813	6.9
12.75			12.34			0.41***	717	7.7
13.46				13.50		-0.04	230	-1.7
13.00					12.10	0.9***	1291	10.4
IOs only:								
15.84					12.99	2.85***	207	10.4
non-IOs only:								
12.10					11.95	0.14***	1084	6.3
non-IOs only, 2011-2012:								
11.85					11.67	0.18***	308	4.2
non-IOs only, 2013-2014:								
12.20					12.07	0.13***	776	4.8

Notes: 1) Table shows the average rating of the entrant vs. the incumbent in the column listed on securities that both CRAs rate. 2) IO is an interest-only security. 3) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 4) Data includes all tranches of CMBS deals rated AAA by at least one CRA issued January 2009 through June 2014 excluding ReREMICS and CDOs.

Table 5: Shopping and the Change in Incumbent Ratings

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			Predicted Shares	
entrant1share	4.37*	3.87	3.91*			
	(2.43)	(2.19)	(2.19)			
entrant2share	3.50***	2.76**	2.80**			
	(1.06)	(1.00)	(1.02)			
pentrant1share				2.18	2.83	2.73
				(4.83)	(4.62)	(4.61)
pentrant2share				2.10**	1.66**	1.68**
				(0.75)	(0.73)	(0.74)
dealshop1		0.20**			0.21**	
		(0.073)			(0.092)	
dealshop2			-0.049			-0.032
			(0.14)			(0.14)
nratings		0.60**	0.61**		0.59**	0.59**
		(0.26)	(0.26)		(0.25)	(0.25)
tranchesize	0.0032**	0.0032**	0.0032**	0.0031**	0.0031**	0.0031**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
subordination	0.33***	0.32***	0.32***	0.33***	0.32***	0.32***
	(0.058)	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)
floater	0.37	0.52	0.51	0.25	0.40	0.39
	(0.38)	(0.44)	(0.44)	(0.41)	(0.46)	(0.45)
variable	-0.41	-0.45	-0.45	-0.39	-0.43	-0.43
	(0.59)	(0.57)	(0.57)	(0.59)	(0.56)	(0.56)
waltv	-0.14***	-0.13***	-0.13***	-0.13***	-0.12***	-0.12***
	(0.026)	(0.024)	(0.025)	(0.028)	(0.026)	(0.026)
wadscr	0.14	0.17	0.16	0.20	0.23	0.22
	(0.14)	(0.13)	(0.13)	(0.16)	(0.15)	(0.15)
wam	0.032***	0.030***	0.030***	0.029***	0.028***	0.028***
	(0.0054)	(0.0055)	(0.0057)	(0.0054)	(0.0055)	(0.0057)
sponsortot	0.000015	0.000012	0.000013	0.000014	0.000011	0.000012
	(9.7e-06)	(0.000011)	(0.000011)	(0.000010)	(0.000011)	(0.000011)
newmonth	-0.092	-0.14	-0.14	-0.12	-0.17	-0.17
	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)	(0.12)
newmonthsq	0.00059	0.0010	0.0011	0.00092	0.0014	0.0014
	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Constant	15.7***	14.8***	14.9***	14.2***	13.6***	13.7***
	(1.64)	(1.47)	(1.46)	(1.77)	(1.64)	(1.63)
Observations	1,610	1,610	1,610	1,610	1,610	1,610
R^2	79%	79%	79%	79%	80%	80%
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
WAL Controls	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Dependent variable is the average rating of the security by incumbent CRAs. 2) $pentrant1share$ and $pentrant2share$ are the predicted entrant market shares as described in the text; see the appendix for the results of the first stage. 3) Standard errors, clustered by dealtype-year, are in parentheses. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 5) Data includes all non-IO tranches of CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 6) See Table 2 for variable definitions.

Table 6: Entrants' Market Shares and Subordination of Tranches Rated AAA by an Incumbent

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			Predicted Shares	
entrant1share	-8.97	-8.85	-8.92			
	(7.13)	(7.04)	(7.07)			
entrant2share	-9.79***	-9.66***	-9.76***			
	(3.09)	(3.12)	(3.13)			
pentrant1share				2.31	2.16	2.35
				(11.9)	(12.0)	(12.0)
pentrant2share				-6.86***	-6.80***	-6.87***
				(1.75)	(1.80)	(1.81)
dealshop1		-0.41*			-0.39*	
		(0.21)			(0.20)	
dealshop2			-0.15			-0.15
			(0.32)			(0.33)
nratings		-0.042	-0.013		-0.0067	0.022
		(0.19)	(0.18)		(0.19)	(0.18)
tranchesize	0.0045*	0.0044*	0.0045*	0.0046**	0.0046**	0.0046**
	(0.0021)	(0.0021)	(0.0021)	(0.0020)	(0.0020)	(0.0020)
floater	0.81	0.80	0.82	0.89	0.87	0.90
	(1.22)	(1.22)	(1.22)	(1.28)	(1.27)	(1.27)
variable	-2.79***	-2.78***	-2.77***	-2.77***	-2.76***	-2.75***
	(0.44)	(0.44)	(0.45)	(0.43)	(0.43)	(0.44)
waltv	0.24**	0.23**	0.24**	0.22**	0.22**	0.22**
	(0.082)	(0.081)	(0.081)	(0.082)	(0.081)	(0.081)
wadscr	0.063	0.060	0.053	-0.044	-0.044	-0.052
	(0.22)	(0.21)	(0.21)	(0.27)	(0.27)	(0.27)
wam	-0.044***	-0.045***	-0.045***	-0.040***	-0.041***	-0.040***
	(0.011)	(0.012)	(0.011)	(0.0093)	(0.0099)	(0.0096)
sponsortot	-0.000023	-0.000022	-0.000022	-0.000018	-0.000017	-0.000017
	(0.000019)	(0.000019)	(0.000018)	(0.000019)	(0.000019)	(0.000019)
newmonth	1.49	1.49	1.49	1.57*	1.56*	1.56*
	(0.85)	(0.85)	(0.85)	(0.83)	(0.83)	(0.83)
newmonthsq	-0.013	-0.013	-0.013	-0.014*	-0.014*	-0.014*
	(0.0079)	(0.0079)	(0.0079)	(0.0077)	(0.0077)	(0.0077)
Constant	-9.13	-8.87	-8.97	-5.27	-5.10	-5.15
	(9.64)	(9.65)	(9.66)	(9.47)	(9.50)	(9.48)
Observations	766	766	766	766	766	766
R^2	74%	74%	74%	75%	75%	75%
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
WAL Controls	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Dependent variable is the subordination level of the security. 2) Only securities rated AAA by at least one incumbent are included. 3) Standard errors, clustered by dealtype-year are in parentheses. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 5) Data includes all non-IO tranches of CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 6) See Table 2 for variable definitions.

Table 7: Effect of Entrants' Market Shares on Incumbent Ratings - IO Tranches

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			Predicted Shares	
entrant1share	1.31	-1.57	-1.20			
	(3.05)	(2.02)	(2.09)			
entrant2share	4.19**	1.46	1.73			
	(1.50)	(1.48)	(1.56)			
pentrant1share				-5.71	-4.36	-5.00
				(5.57)	(4.44)	(4.21)
pentrant2share				2.77***	1.35	1.46
				(0.73)	(1.09)	(1.13)
dealshop1		0.77**			0.70**	
		(0.29)			(0.29)	
dealshop2			0.0050			-0.010
			(0.33)			(0.32)
nratings		2.31***	2.29***		2.29***	2.27***
		(0.70)	(0.67)		(0.72)	(0.69)
floater	3.93	4.87	4.70	4.09	5.37	5.21
	(4.18)	(4.69)	(4.79)	(3.91)	(4.51)	(4.59)
variable	4.75**	3.45*	3.49*	4.76**	3.57*	3.61*
	(1.95)	(1.65)	(1.69)	(1.94)	(1.69)	(1.72)
waltv	0.023	0.043	0.042	0.027	0.045	0.044
	(0.051)	(0.048)	(0.049)	(0.050)	(0.047)	(0.048)
wadscr	0.20	0.38	0.37	0.23	0.41	0.39
	(0.13)	(0.24)	(0.25)	(0.15)	(0.24)	(0.25)
wam	0.030***	0.021*	0.020*	0.028***	0.019*	0.019*
	(0.0088)	(0.010)	(0.010)	(0.0086)	(0.0097)	(0.0098)
sponsortot	-0.000046**	-0.000043*	-0.000043*	-0.000048**	-0.000044*	-0.000043*
	(0.000017)	(0.000021)	(0.000023)	(0.000017)	(0.000022)	(0.000024)
newmonth	0.042	-0.19	-0.19	0.041	-0.16	-0.16
	(0.13)	(0.18)	(0.18)	(0.12)	(0.17)	(0.17)
newmonthsq	0.00020	0.0019	0.0020	0.00020	0.0017	0.0017
	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0014)	(0.0015)
Constant	3.10	3.76	3.81	1.81	3.18	3.10
	(4.89)	(6.25)	(6.32)	(4.81)	(6.24)	(6.26)
Observations	349	349	349	349	349	349
R^2	22%	34%	34%	22%	34%	33%
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Dependent variable is the average rating of the security by incumbent CRAs. 2) $pentrant1share$ and $pentrant2share$ are the predicted entrant market shares as described in the text; see table above for results of the first stage. 3) Standard errors, clustered by dealtype-year, are in parentheses. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 5) Data includes all IO tranches of CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 6) See Table 2 for variable definitions.

Figure 1: Share of Securities Rated by CRAs over Time

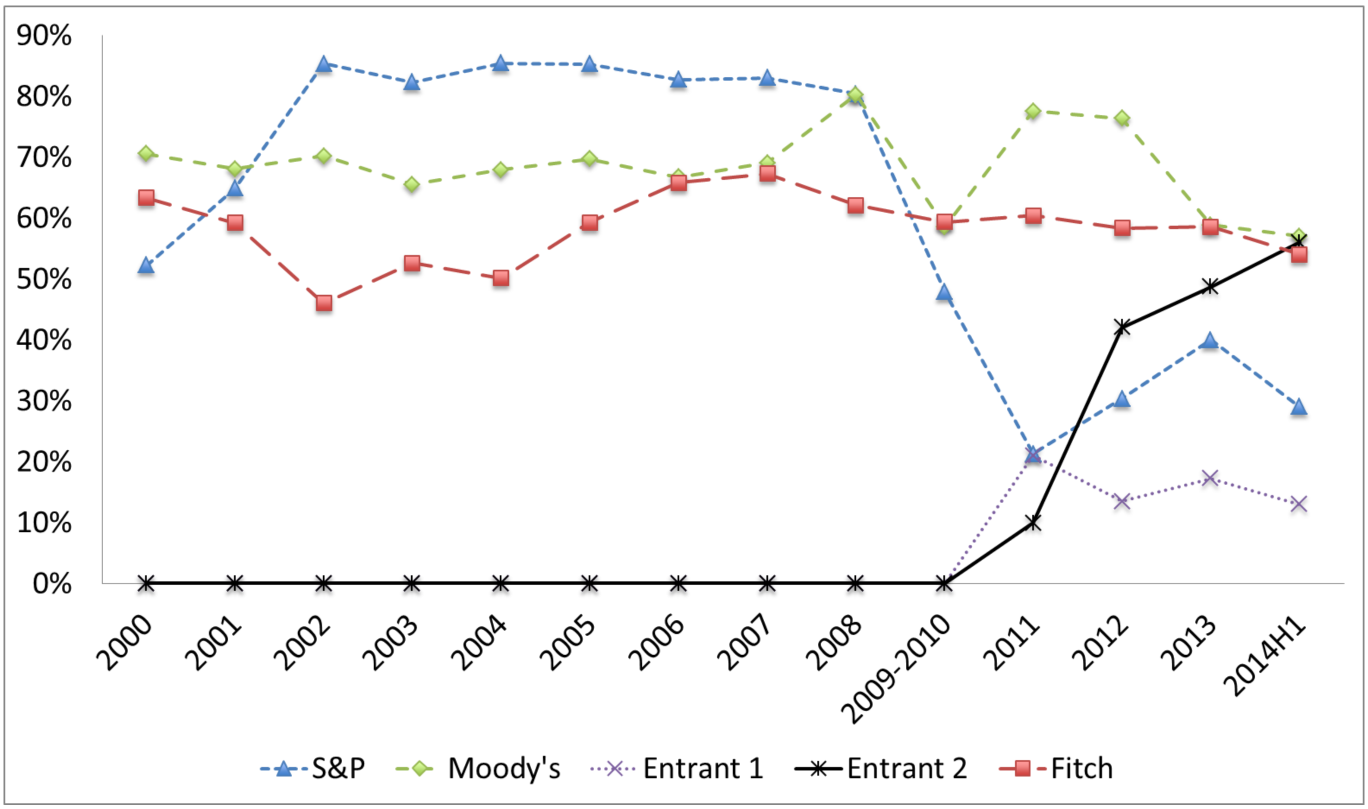
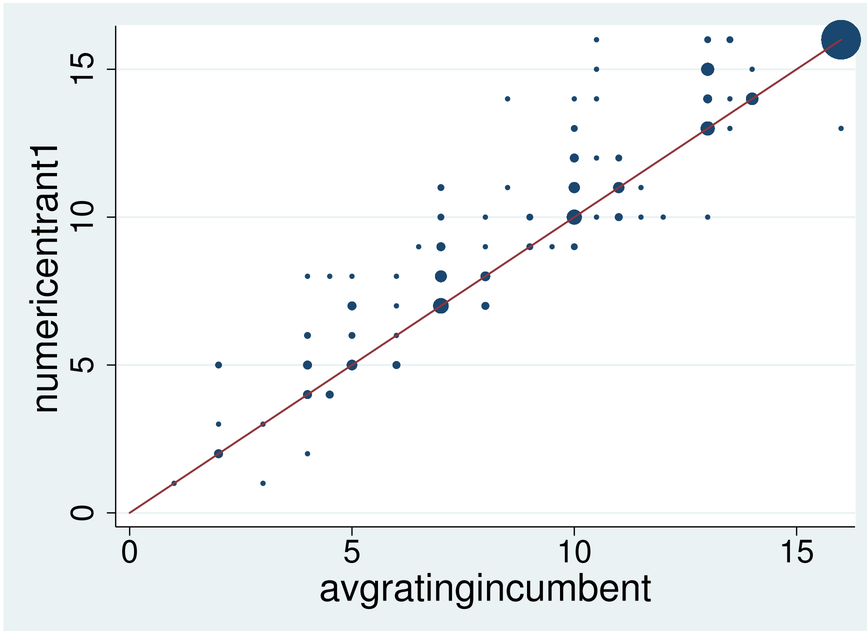
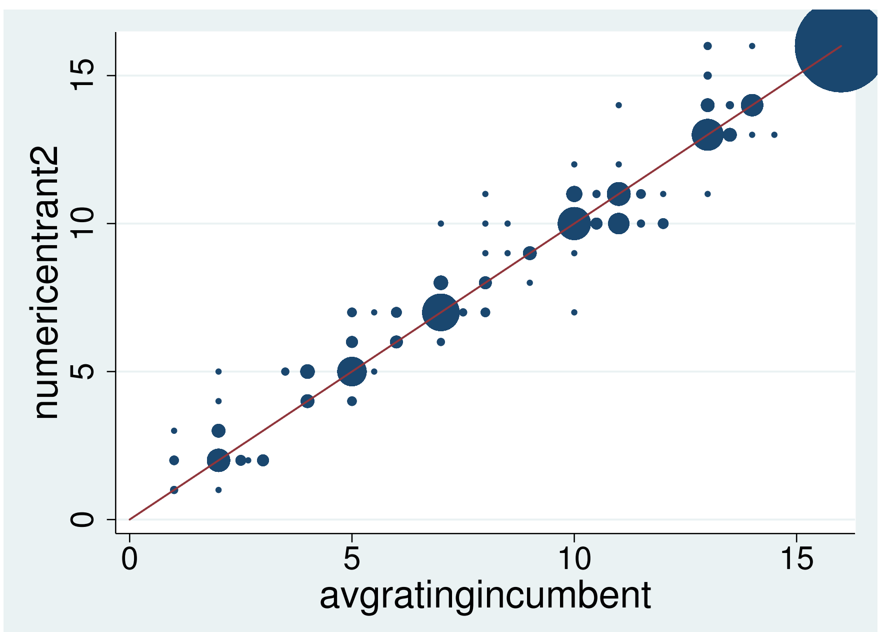


Figure 2: Entrants vs. Incumbent CRAs Average Ratings on non-IO Securities



(a) Entrant 1



(b) Entrant 2

Notes: 1) Numeric Ratings: 16=AAA, 1=B-. 2) The figure plots ratings of entrants against average rating of incumbent on the same security. 3) Dots are frequency-weighted.

A Supplementary Material (Not-for-Publiction)

Table A.1: Rating Definitions for AAA

S&P	The obligor's capacity to meet its financial commitment on the obligation is extremely strong.
Moody's	Financial obligations assessed aaa (sca) are judged to have the highest credit quality and thus subject to the lowest credit risk, when used as inputs in determining a structured finance transaction's rating.
Fitch	"AAA" ratings denote the lowest expectation of default risk. They are assigned only in cases of exceptionally strong capacity for payment of financial commitments. This capacity is highly unlikely to be adversely affected by foreseeable events.
DBRS	Highest credit quality. The capacity for the payment of financial obligations is exceptionally high and unlikely to be adversely affected by future events.
Entrant 1	A rating of "AAA" is the highest letter-grade assigned by Morningstar. Securities rated "AAA" have an extremely strong ability to make timely interest payments and ultimate principal payments on or prior to a rated final distribution date.
Entrant 2	Determined to have almost no risk of loss due to credit-related events. Assigned only to the very highest quality obligors and obligations able to survive extremely challenging economic events.

Notes: 1) S&P and DBRS do not have rating definitions specific to structured finance; the appropriate scale for structured finance for these CRAs is 'long-term obligation'. 2) Sources are the CRA's most recent publication of rating definitions: (Standard & Poor's 2009, Moody's Investors Service 2014, FitchRatings 2014, DBRS 2013, Morningstar Credit Ratings, LLC 2012, and Kroll Bond Ratings 2014). 3) Moody's changed its rating definition for structured finance in 2014 relative to 2009; the definition in the 2009 publication (Moody's Investors Service 2009) uses similar language to the definition in the 2014 publication.

Table A.2: Share of Securities Rated by Entrants

Year	2009	2010	2011	2012	2013	2014H1	Total
Panel A: All Deal Types							
ratedentrant1	0%	0%	21%	13%	17%	13%	15%
ratedentrant2	0%	0%	10%	42%	49%	56%	40%
ratedentrant	0%	0%	31%	49%	63%	62%	52%
Panel B: Conduit/Fusion Deals							
ratedentrant1	0%	0%	24%	5%	6%	13%	9%
ratedentrant2	0%	0%	2%	40%	66%	61%	47%
ratedentrant	0%	0%	26%	45%	70%	68%	54%
Panel C: Large Loan Deals							
ratedentrant1	0%	0%	18%	29%	45%	15%	31%
ratedentrant2	0%	0%	39%	46%	18%	43%	29%
ratedentrant	0%	0%	57%	61%	57%	50%	53%
Panel D: Other Deals							
ratedentrant1	0%	0%	0%	41%	0%	0%	10%
ratedentrant2	0%	0%	0%	50%	2%	0%	13%
ratedentrant	0%	0%	0%	50%	2%	0%	13%

Table A.3: Issues An Entrant Rates and Incumbent Ratings

	(1)	(2)	(3)	(4)
	Non-IO Securities		IO Securities	
avgincumerror	0.022		0.024	
	(0.015)		(0.020)	
incumlow		-0.11*		-0.058
		(0.068)		(0.15)
tranchesize	-0.00029	-0.00025		
	(0.00033)	(0.00033)		
subordination	0.0040	0.0039		
	(0.0040)	(0.0040)		
floater	-0.39*	-0.39*		
	(0.20)	(0.20)		
variable	-0.077	-0.072	0.17	0.21
	(0.094)	(0.094)	(0.51)	(0.52)
wal3to5	0.18	0.17		
	(0.15)	(0.15)		
wal5to7	-0.0038	-0.0035		
	(0.18)	(0.18)		
walover7	0.13	0.11		
	(0.14)	(0.14)		
waltv	-0.0061	-0.0068	0.0030	0.0030
	(0.0093)	(0.0093)	(0.017)	(0.017)
wadscr	-0.033	-0.033	-0.060	-0.056
	(0.072)	(0.072)	(0.12)	(0.12)
wam	0.0030	0.0031	0.0082	0.0083*
	(0.0031)	(0.0031)	(0.0050)	(0.0051)
sponsortot	3.9e-06	4.1e-06	-2.6e-08	-2.4e-07
	(4.9e-06)	(4.9e-06)	(9.9e-06)	(9.9e-06)
Constant	-0.0097	0.092	-1.17	-1.20
	(0.81)	(0.81)	(1.55)	(1.55)
Year of Issue FEs	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes
Observations	1,538	1,538	330	330
Pseudo R^2	9%	9%	10%	9%

Notes: 1) Dependent variable takes a value of 1 if the entrant rates it, 0 otherwise. 2) The main variables of interest are *avgincumerror* and *incumlow*. 3) *avgincumerror* is the average incumbent rating of a security less the prediction of the rating from a regression of the incumbents' ratings over the period 2011-2014. 4) *incumlow* takes a value of 1 if *avgincumerror* < 0. 5) Standard errors are in parentheses. 6) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 7) See Table 2 for variable definitions.

Table A.4: Precision of Rating Models Across CRAs

CRA	All Deal Types	All Deal Types 2012Q4-	Conduit / Fusion	Large Loans	IOs	IOs 2012Q2-
S & P	79%	81%	88%	84%	33%	37%
Moody's	79%	84%	85%	90%	5%	10%
Fitch	81%	84%	86%	91%	16%	15%
Entrant 1	80%	85%	81%	93%	*	*
Entrant 2	85%	87%	90%	94%	28%	28%
Year of Issue FEs	No	No	No	No	No	No
Deal Type FEs	Yes	Yes	No	No	Yes	Yes
Collateral Controls	Yes	Yes	Yes	Yes	Yes	Yes
Coupon Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
WAL Controls	Yes	Yes	Yes	Yes	No	No
Subordination Control	Yes	Yes	Yes	Yes	No	No

Notes: 1) The table presents the R^2's from a regression of the numeric rating on security characteristics for securities issued from 2011-2014. 2) * Denotes too few observations (fewer than 60) to estimate reliably.

Table A.5: First Stage Probit Estimation for Predicted Entrant Market Shares Approach

	(1) *ratedentrant1*	(2) *ratedentrant2*
floater	-0.81***	0.19
	(0.17)	(0.15)
variable	-0.031	-0.067
	(0.084)	(0.068)
IO	-0.14	-0.019
	(0.11)	(0.091)
posterisa	0.84***	0.20*
	(0.16)	(0.12)
entrant2out	1.05***	-0.73***
	(0.15)	(0.21)
newmonth	0.084***	0.26***
	(0.025)	(0.029)
newmonthsq	-0.0011***	-0.0023***
	(0.00031)	(0.00032)
Constant	-3.79***	-7.08***
	(0.57)	(0.69)
Observations	2,178	2,178
Year of Issue FEs	No	No
Deal Type FEs	Yes	Yes
Geog. Controls	Yes	Yes
Prop. Type Controls	Yes	Yes
Pseudo R-squared	15%	19%

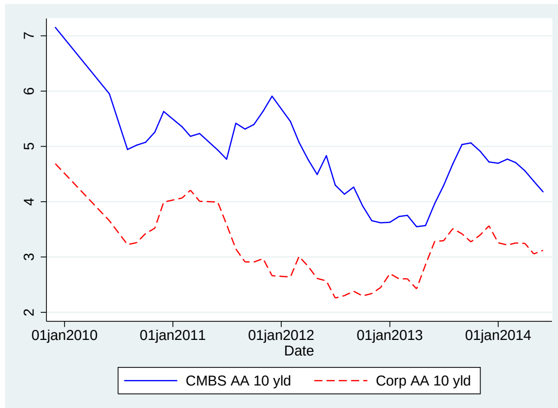
Notes: 1) Dependent variable in columns 1 and 2 takes a value of 1 if entrant 1 or entrant 2 rates the security, respectively. 2) Standard errors are in parentheses. 3) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 5) Data includes tranches of CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 4) See Table 2 for variable definitions.

Table A.6: Entrants' Market Shares and Incumbent Ratings, Additional Specifications

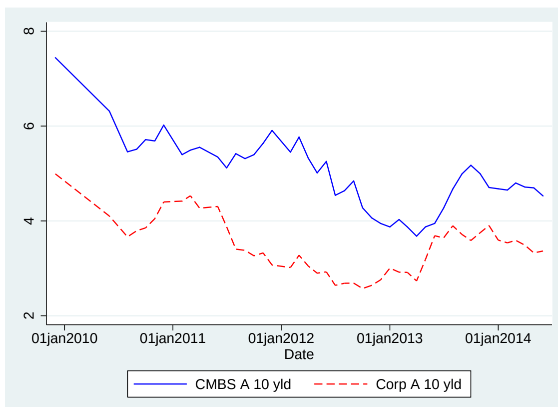
	(1)	(2)	(3)	(4)	(5)	(6)
		avgratingincumbent		*numericsp*	*numericmoodys*	*numericfitch*
	OLS	Ord. Probit	Pred. Shares			
entrant1share	4.37*	2.74*		7.91***	5.07	7.80**
	(2.43)	(1.40)		(2.47)	(4.12)	(2.89)
entrant2share	3.50***	1.89***		2.71*	7.02*	4.82*
	(1.06)	(0.62)		(1.34)	(3.27)	(2.32)
pentrant1share			2.18			
			(4.83)			
pentrant2share			2.10**			
			(0.75)			
tranchesize	0.0032**	0.013***	0.0031**	0.0041**	0.0018	0.0024
	(0.0013)	(0.0052)	(0.0013)	(0.0016)	(0.0013)	(0.0019)
subordination	0.33***	0.17***	0.33***	0.24***	0.37***	0.40***
	(0.058)	(0.043)	(0.057)	(0.035)	(0.048)	(0.054)
floater	0.37	0.45	0.25	0.99	0.13	0.42
	(0.38)	(0.39)	(0.41)	(0.59)	(0.49)	(0.72)
variable	-0.41	-0.20	-0.39	-1.01**	-0.36	0.21
	(0.59)	(0.20)	(0.59)	(0.46)	(0.54)	(0.60)
waltv	-0.14***	-0.091***	-0.13***	-0.091*	-0.20***	-0.14***
	(0.026)	(0.022)	(0.028)	(0.049)	(0.047)	(0.031)
wadscr	0.14	0.056	0.20	0.58***	-0.18	-0.17
	(0.14)	(0.066)	(0.16)	(0.10)	(0.12)	(0.53)
wam	0.032***	0.022***	0.029***	0.045***	0.041***	-0.0024
	(0.0054)	(0.0043)	(0.0054)	(0.011)	(0.0061)	(0.010)
sponsortot	0.000015	5.7e-06	0.000014	0.000013	0.000023**	2.5e-06
	(9.7e-06)	(8.5e-06)	(0.000010)	(0.000019)	(7.6e-06)	(0.000014)
newmonth	-0.092	0.079	-0.12	0.69**	-0.41***	-0.22
	(0.13)	(0.083)	(0.13)	(0.29)	(0.13)	(0.17)
newmonthsq	0.00059	-0.0012	0.00092	-0.0068**	0.0044***	0.0018
	(0.0014)	(0.00094)	(0.0013)	(0.0027)	(0.0013)	(0.0017)
Constant	15.7***		14.2***	6.13*	21.0***	20.4***
	(1.64)		(1.77)	(3.30)	(3.92)	(3.31)
Observations	1,610	1,610	1,610	504	1,143	1,022
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
WAL Controls	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes
R^2	79%		79%	81%	81%	82%
Pseudo-R^2		38%				

Notes: 1) Dependent variable in columns (1)-(3) is the average rating of the security by incumbent CRAs. 2) Dependent variable in columns (4)-(6) is the rating of the security by each of the main incumbent CRAs. 3) *pentrant1share* and *pentrant2share* are the predicted entrant market shares as described in the text; see the appendix for the results of the first stage. 4) Standard errors, clustered by dealtype-year, are in parentheses. 5) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 6) Data includes all non-IO tranches of CMBS deals issued January 2009 through June 2014 excluding ReREMICS and CDOs. 7) See Table 2 for variable definitions.

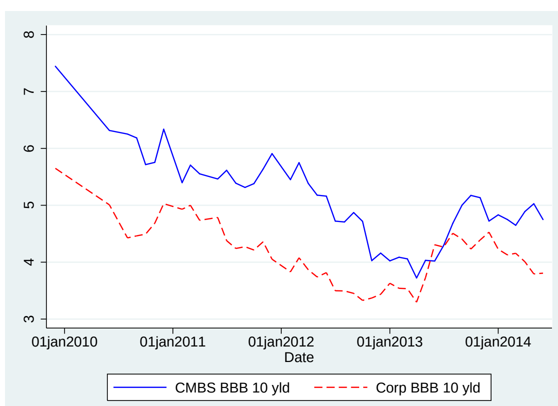
Figure A.1: Interest Rates on CMBS vs. Corporates



(a) AA



(b) A



(c) BBB

Notes: 1) Ratings for CMBS are ratings by incumbent CRAs. 2) Corporate bond yields come from Bloomberg's composite yield indices, which are constructed daily using all bonds that have Bloomberg Valuation prices at market close. 3) CMBS yields are the coupon at issuance averaged by quarter for CMBS with WAL between 9 and 15 years.

Market Valuation of Entrant Ratings

Given that the entrants are more likely to issue AAA ratings, a natural question is whether the market discounts these ratings. To test whether investors treat AAA ratings from entrants and incumbents differently, we estimate

$$cpnspread_{i,j,t} = \alpha_0 + \alpha_1 AAAentrantonly_{i,j,t} + \alpha'_{\mathbf{x}} Controls_{i,j,t} + \epsilon_{i,j,t} \tag{9}$$

on the set of securities that are rated AAA by at least one CRA and

$$cpnspread_{i,j,t} = \beta_0 + \beta_1 AAAtwowithentrant_{i,j,t} + \beta'_{\mathbf{x}} Controls_{i,j,t} + \epsilon_{i,j,t} \tag{10}$$

on the set of securities rated by exactly two CRAs where both ratings are AAA. In equation (9), $AAAentrantonly$ takes a value of 1 if only an entrant rates it AAA. In equation (10), $AAAtwowithentrant$ takes a value of 1 if at least one of the two AAA ratings is from an entrant. $cpnspread_{i,j,t}$ is the initial coupon spread over comparable maturity Treasuries as a proxy. To compute this spread, we use the WAL as the security's maturity and subtract off the yield on a treasury of comparable maturity in the month the security is issued.[15]

In equations (9) and (10), i indexes the security, j indicates the deal type, and t indicates the year of issuance. The controls include dummies for the year of issue, deal type dummies, collateral characteristics, dummies for the coupon type (fixed rate, floating rate, or variable rate), and the *ex ante* WAL of the security in categories. If investors perceive the entrants' ratings to be a less reliable indicator of quality than the incumbents', they will demand a higher return for an issue rated AAA by only an entrant ($AAAentrantonly = 1$). Similarly, if investors find incumbent ratings more credible than those of entrants, it will treat a security rated AAA by less than two incumbents ($AAAtwowithentrant = 1$) riskier than a security rated AAA by two incumbents. A finding that $\alpha_1 > 0$ or $\beta_1 > 0$ thus indicates that investors

[15] The actual legal maturity dates for CMBS are usually 30-40 years after issuance although that does not represent the true final payment date expected by investors.

do not treat ratings from entrants and incumbents equally.

Column 1 of Table A.7 contains the results of estimating (9) on securities of all coupon types. The coefficient on $AAAentrantonly$ is positive but statistically insignificant. Because the effect of the covariates may differ depending on whether the coupon is fixed rate, variable, or floating, in Column 2 we estimate (9) using only the subset of securities that have a fixed rate coupon while in column 3 we estimate the model using only securities that have variable or floating rate coupons. In Column 2, the coefficient on $AAAentrantonly$ indicates that a security rated AAA by only an entrant must pay investors roughly 39 basis points more than a security rated AAA by at least one incumbent, but the effect is statistically insignificant.

Columns 3 and 4 of Table A.7 present the findings from estimating (10) on all securities with exactly two AAA ratings. In Column 3, which includes securities of all coupon types, $\beta_1 > 0$ is positive but only borderline significant at the 10 % level. The magnitude indicates that securities that have at least one of their AAA ratings from an entrant must pay investors 19 basis points more than securities that two incumbents rates AAA. When we estimate (10) separately for securities with fixed coupons, the coefficient continues to be positive, of similar magnitude, and is statistically significant at the 10% level.

Thus, it appears that investors treat AAA ratings from entrants differently than those of incumbents. The statistical evidence is admittedly not strong but the consistency of the signs across specifications suggests there may be some discounting of entrant ratings.

Table A.7: *AAA* Yields and Securities Rated *AAA* by Entrants

	(1)	(2)	(3)	(4)
AAAentrantonly	0.18	0.39		
	(0.24)	(0.31)		
AAAtwowithentrant			0.19	0.23*
			(0.12)	(0.12)
tranchesize	-0.00044***	-0.00039***	-0.00052***	-0.00055***
	(0.000092)	(0.000088)	(0.00019)	(0.00018)
subordination	-0.011***	-0.0088**	-0.0061	0.00083
	(0.0034)	(0.0035)	(0.0065)	(0.0064)
floater	0.023		0.036	
	(0.13)		(0.40)	
variable	0.34***		0.38***	
	(0.045)		(0.11)	
wal3to5	0.46***	0.57***	0.40***	0.60***
	(0.043)	(0.040)	(0.096)	(0.090)
wal5to7	0.64***	0.66***	0.66***	0.74***
	(0.054)	(0.049)	(0.13)	(0.12)
walover7	0.62***	0.66***	0.60***	0.72***
	(0.039)	(0.035)	(0.087)	(0.079)
waltv	0.0100**	0.0017	0.0034	-0.0046
	(0.0040)	(0.0045)	(0.0080)	(0.0098)
wadscr	-0.036	-0.13**	-0.10	-0.23
	(0.034)	(0.054)	(0.061)	(0.16)
wam	0.0011	0.00050	0.0012	0.00010
	(0.0012)	(0.0011)	(0.0030)	(0.0027)
sponsortot	-2.6e-06	-5.0e-07	-3.5e-06	-3.4e-06
	(1.8e-06)	(1.9e-06)	(4.4e-06)	(4.9e-06)
Constant	0.95**	1.59***	1.47*	1.67*
	(0.38)	(0.43)	(0.80)	(0.87)
Year of Issue FEs	Yes	Yes	Yes	Yes
Deal Type FEs	Yes	Yes	Yes	Yes
Geog. Controls	Yes	Yes	Yes	Yes
Prop. Type Controls	Yes	Yes	Yes	Yes
Coupon Type	All	Fixed	All	Fixed
Observations	741	645	240	201
R^2	54%	55%	54%	56%

Notes: 1) Dependent variable is the spread on the security relative to a US treasury of comparable maturity. 2) The main variable of interest in Columns (1) and (2) is *AAAentrantonly* which takes a value of 1 if only an entrant rates the security AAA. The main variable of interest in Columns (3) and (4) is *AAAtwowithentrant* which takes a value of 1 if at least one of the *AAA* ratings is from an entrant. 3) Standard errors are in parentheses. 4) $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. 5) Data in Columns (1) and (2) includes all non-IO tranches of CMBS deals rated *AAA* by at least one CRA issued January 2009 through June 2014 excluding ReREMICS and CDOs. Data in Columns (3) and (4) includes all tranches of CMBS rated *AAA* by exactly two CRAs that are also rated by exactly two CRAs. 6) See Table 2 for variable definitions.

Security Performance

Tables A.8 and A.9 report summary statistics performance for the securities in our estimation sample. Given the low degree of seasoning, we do not observe any meaningful principal losses and/or interest shortfalls. Table A.8 reports current cumulative principal losses on the *deal* as a percentage of deal size, by year. Only the 2011 vintage tranches exhibit any kind of principal loss at this point, and those losses are too small to reach into any of the investment grade tranches at this point. The average cumulative loss is less than 0.01% of deal size, and the median is 0.0%. Beyond 2011, there are no reported principal losses.

Interest shortfalls for the estimation sample securities are also negligible. Table A.9 reports the cumulative shortfalls on the *securities* in dollars. Only 0.3% and 0.4% of the securities issued in 2011 and 2012 have any interest shortfalls.

Table A.8: Cumulative principal losses (% of total deal size)

Year	Obs.	Mean	Std. Dev.	Min	Max	% of total
2009	11	0	0	0	0	0.00%
2010	105	0	0	0	0	0.00%
2011	308	0.006	0.04	0	0.3	9.60%
2012	533	0	0	0	0	0.00%
2013	974	0	0	0	0	0.00%
2014:H1	449	0	0	0	0	0.00%

Notes: 1) Cumulative principal loss is as a percentage of total deal size. 2) The column "% of total" represents the percentage of securities in each year that had nonzero (and nonmissing) cumulative principal losses.

Table A.9: Cumulative interest shortfall

Year	Obs.	Mean	Std. Dev.	Min	Max	% of total
2009	15	3.27	12.66	0	49.02	3.60%
2010	107	0.46	4.74	0	49	0.90%
2011	325	38.3	690.38	0	12446	0.30%
2012	539	0.32	5.26	0	97.16	0.40%
2013	982	0	0	0	0	0.00%
2014:H1	446	0	0	0	0	0.00%

Notes: 1) Cumulative interest shortfall is in dollars. 2) The column "% of total" represents the percentage of securities in each year that had nonzero (and nonmissing) cumulative interest shortfalls.

Loan-Level Collateral Performance

In addition to interest shortfalls and/or principal losses for the bonds, we are also interested in the performance of the underlying collateral. Every deal in our sample is comprised of a single collateral group, so we measure the performance at the deal level. Our data contains the most recent[16] percentage of loans which are 90 or more days delinquent, including loans in foreclosure, bankruptcy, and those that are real estate owned (REO). We also observe the percentage that are just 90 or more days delinquent.[17]

Tables A.10 and A.11 report deal-level summary statistics for these measures, by year of issuance.[18] The two measures are very similar in distribution, indicating that the number of loans that are in bankruptcy, foreclosure, or REO status is small. Consistent with the data on individual bond performance, 2011 vintage deals display the largest amount of delinquent loans, with an average of 0.13%. The 2012 and 2013 deals also have some poorly-performing collateral, but overall the amount of delinquencies in the sample as a whole is not material.

Table A.10: Percentage of loans 90+ days delinquent, plus bankruptcy, foreclosure and REO status

Year	Obs.	Mean	Std. Dev.	Min	Max	% of total
2009	4	0	0	0	0	0%
2010	17	0	0	0	0	0%
2011	30	0.13	0.38	0	1.9	17%
2012	59	0.09	0.4	0	1.9	7%
2013	100	0.06	0.32	0	1.9	4%
2014:H1	49	0	0	0	0	0%
Total	259	0.06	0.3	0	1.9	5%

Notes: 1) Data is at the deal level. 2) The column "% of total" represents the percentage of securities in each year that had nonzero (and nonmissing) values of 90 day delinquent plus bankrupt, foreclosed, and REO.

[16]For the vast majority of securities this is May 2014 or later.

[17]We also observe similar measures for 60 days, but we do not report these because they are nearly identical, both statistically and economically, to the 90 day measures.

[18]We winsorize at the 99% level due to a single large outlier.

Table A.11: Percentage of loans 90+ days delinquent

Year	Obs.	Mean	Std. Dev.	Min	Max	% of total
2009	2	0	0	0	0	0%
2010	15	0	0	0	0	0%
2011	28	0.11	0.35	0	1.77	13%
2012	55	0.03	0.22	0	1.64	2%
2013	99	0.06	0.31	0	1.77	4%
2014:H1	49	0	0	0	0	0%
Total	248	0.04	0.25	0	1.77	4%

Notes: 1) Data is at the deal level. 2) The column "% of total" represents the percentage of securities in each year that had nonzero (and nonmissing) values of 90 days delinquent.

References Specific to Supplementary Material

DBRS, 2013. Rating Scales: Long Term Obligations Scale.

FitchRatings, 2014. Definitions of Ratings and Other Forms of Opinion.

Kroll Bond Ratings, 2014. Rating Scales: Long-Term Credit. No date provided on html document; last accessed on August 18, 2014 at https://www.krollbondratings.com/ratings/scales.

Moody's Investors Service, 2009. Moody's Rating Symbols & Definitions.

Moody's Investors Service, 2014. Rating Symbols and Definitions.

Morningstar Credit Ratings, LLC, 2012. Form NRSRO Exhibit 2.

Standard & Poor's, 2009. General Criteria: Understanding Standard & Poor's Rating Definitions.