Does the Market Understand Rating Shopping? Predicting MBS Losses with Initial Yields

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We study rating shopping on the MBS market. Outside of AAA, losses are higher on single-rated tranches than on multi-rated ones, and yields predict future losses for single-rated tranches, but not for multi-rated ones. Conversely, ratings have less explanatory power for single-rated tranches. These results suggest that single-rated tranches have been "shopped," whereby pessimistic ratings never reach the market. For AAA-rated MBS, by contrast, 93% receive two or three such ratings, and those ratings agree 97% of the time. This ratings convergence suggests that agencies "cater" to investors, who cannot purchase a tranche unless it has multiple AAA ratings. (*JEL* G21, G24, G28, G1, L1)

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There is growing evidence revealing problems in the practice of credit rating agencies, especially in the structured finance markets including mortgage-backed securities (MBS). The root cause stems from a potential conflict of interest: instead of being rewarded by "consumers" for high-quality ratings, rating agencies are paid by issuers. Therefore, critics stipulate that agencies may face pressure to grant inflated ratings to compete for business despite a possible loss of reputation (e.g., Bolton, Freixas, and Shapiro 2012; Bar-Isaac and Shapiro 2013). Regulations contingent on ratings may further distort the

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incentives of both issuers and agencies: holding highly rated MBS securities lowers the burden of capital requirements for financial institutions (e.g., Acharya and Richardson 2009; Acharya, Schnabl, and Suarez 2013), while other institutional investors (e.g., pension funds) are constrained to hold safe fixed income assets as certified by multiple AAA ratings.

The perverse incentives of issuers and rating agencies can affect the quality of ratings through the process of "rating shopping," whereby issuers only purchase and report the most favorable rating(s) after receiving preliminary opinions from multiple agencies (e.g., Mathis, McAndrews, and Rochet 2009; Skreta and Veldkamp 2009; Opp, Opp, and Harris 2013).[1] Since issuers are not required to disclose preliminary contacts with rating agencies, shopping tends to be hidden from view (e.g., Sangiorgi and Spatt 2010; Fulghieri, Strobl, and Xia 2014); yet, it can influence the distribution and information content of ratings revealed to investors. Shoppers may censor out pessimistic ratings, thus reducing the number of ratings observed empirically and, at the same time, reducing the likelihood of observed ratings disagreements. Consistent with this idea, He, Qian, and Strahan (2012) show that initial yields were higher for MBS tranches with just one rating, controlling for the level of the rating and other measures of risk. Even with more than one, ratings may converge due to the threat of shopping and may be particularly pronounced in the AAA segment, where investors constrained by regulations or contractual terms cannot purchase a tranche unless it has at least two such ratings. Beyond the number of ratings, earlier research (He, Qian, and Strahan 2012) finds that market yields were also higher on MBS sold by large issuers, suggesting that investors at least partially understood and priced the risk that large issuers used their bargaining power to receive inflated ratings.[2]

In this paper, we test a joint hypothesis: (1) market participants understand that ratings shopping can lead agencies to inflate ratings and one-rated tranches are more likely to have been shopped, and (2) given these concerns, ratings can no longer capture risk well, so investors go beyond the ratings in setting prices. We do so by linking cumulative losses through 2012 to initial yields, conditional on the rating (and other observables). If the market rationally suspects poor-quality or inflated ratings, then initial yields ought to explain ex post performance, and that explanatory power ought to be greater for tranches with just one rating. Absent such concerns, yields should have less (or no) power to explain defaults conditional on the rating. The alternative hypothesis—that market participants trust the integrity of the ratings

[1] Although they do not focus on ratings, see Alexander et al. (2002) and Ashcraft and Schuermann (2008) for a description of the subprime mortgage business.

[2] A number of studies have also tested how the tranching structure, such as the amount of a sponsor's investment in subordinated tranches, forecasts future outcomes (e.g., Demiroglu and James 2012; Begley and Purnanadam 2013).

process—thus implies that ratings offer a sufficient statistic for credit risk; hence, initial yields ought to have no incremental power to explain future outcomes.

To test these ideas, we match a large sample of privately issued (non-GSEs) MBS tranches sold between 2000 and 2006 with information on the initial yield (at issuance), rating history (from Moody's, S&P and Fitch), and cumulative losses (the percentage of principal balance write-offs due to default through June 2012). Default rates rise dramatically for tranches sold during the market boom years (2004–2006), as compared with earlier years (2000–2003). AAA tranches, which account for 89.4% of the total funding in our sample, have very low default rates in most years: tranches sold in 2006 (2005) have an average default rate of 5.3% (1%), and in all other years, the median default rate is zero. Tranches whose highest ratings are AAA (or equivalent) have two or three such ratings more than 93% of the time. Outside of AAA, however, a much higher percentage of tranches receive just one rating (nearly one-third), and the default rates of the single-rated tranches exceed those with two or three ratings. For example, conditional on ratings, we find default rates are 18.1% higher for one-rated tranches compared to similarly rated tranches with two or three ratings. These facts suggest that in the AAA market, rather than dropping pessimistic ratings, the threat of rating shopping leads to convergence. This pattern suggests that rating agencies have catered to investors in the AAA market, who cannot purchase a tranche unless it has at least two AAA ratings.[3] In the non-AAA market, in contrast, shopping seems to lead issuers to drop the more pessimistic ratings, perhaps because many of the investors are less likely to require multiple ratings for regulatory or contractual compliance.[4]

To test for the information content in yields, we regress ex post loss rates on the log of yield spread at issuance. In the non-AAA market, initial yields predict future losses for tranches, most strongly for those sold by large issuers and for those with a single rating. These results indicate that when investors are concerned about the integrity of the ratings process, pricing embeds information about risk that goes beyond the credit rating. Whether or not the risks associated with ratings shopping are correctly priced, however, is more difficult to assess. The data are generated by a large tail event—the housing boom and crash—so it is unrealistic to think that defaults during this period reflect expected losses.

[3] In fact, Griffin, Nickerson and Tang (2013) provide direct evidence of catering; they show that the rating agencies adjusted the amount of funds within a deal receiving the AAA-rating from that implied by their quantitative models to match the AAA-fraction offered by the competing agency. Their evidence suggests that competitive pressure, combined with issuer bargaining power from the threat of ratings shopping, created a race to the bottom.

[4] Bongaerts, Cremers, and Goetzmann (2012) find that an increased likelihood of having a Fitch rating in cases in which Moody's and S&P disagree over whether or not a bond is investment grade. They interpret Fitch as acting as a tie breaker that leads to two investment grade ratings, which is required for many investors. Becker and Ivashina (2015) show that insurance companies, who tend to hold very highly rated bonds due to capital regulations, offset some of the effects of these regulations by reaching for yield, meaning they tend to hold high-yield bonds within a rating category.

Nevertheless, the results do indicate that investors in the lower-rated segments of the MBS market incorporated information in addition to ratings in pricing the securities.

In the AAA market, in contrast, yields are much less correlated with defaults (and not at all in some models), and the effect does not interact with one rating. Given the scale of the AAA market, which funded the vast majority of MBS, this result suggests the market was dominated by naïve investors who relied exclusively on ratings.

Further, we compare the information content in the non-AAA market of ratings with that of yields. To do so, we map the discrete ratings at issuance into the *Expected default frequency* (*EDF*). We find that *EDF*'s ability to forecast future losses is lower among one-rated tranches and declines with issuer size; conversely, the power of yields to forecast losses is higher among one-rated tranches and increases with issuer size. For tranches sold by small issuers with multiple ratings (where ratings ought to be accurate), a change in *EDF* consistent with moving from A to BBB explains all of the variation in future defaults (i.e., yields have no explanatory power in such cases). At the opposite extreme—tranches sold by large issuers with a single rating—the same change in *EDF* explains 25% of the variation in future defaults (with the other 75% explained by yields). These results suggest that market yields become more important when ratings are less informative because the integrity of the process has been compromised. The results also support and extend those in our earlier findings (He, Qian, and Strahan 2011, 2012). There, we show that yields are higher for single-rated tranches and tranches sold by large issuers, arguing that investors rationally feared that rating agencies had granted more inflated ratings to these tranches.

Our paper extends the literature on the quality of ratings in structured finance. These are important questions, not only because ratings play a key role in all fixed income markets in part due to agencies' access to private information but also because the regulation of large financial institutions depends on the accuracy of ratings. While Griffin and Tang (2012) and He, Qian, and Strahan (2012) examine how the incentive problems of rating agencies affect the subordination and pricing of structured finance products, we link the "outcome"—ex post losses of MBS—to ex ante pricing of these securities. Adelino (2009) also finds that ex ante yields help explain ex post performance (future rating downgrades, not actual realized losses examined here) of MBS tranches, but he does not examine how this predictability varies with the market's assessment of rating shopping based on the number of reported ratings and rating categories. Benmelech and Dlugosz (2009) also find that CDOs (including MBS) with one rating are more likely to be downgraded and link this finding to shopping, but they do not test whether the market understands this problem (i.e., how yields forecast future losses), as we do. Our paper is the first to compare the explanatory power of ratings versus yields for subsequent default and to link that relative power to plausible measures of the quality of the ratings process.[5]

1. Data and Methods

Our sample of privately issued residential MBS deals is obtained from Bloomberg. We begin the data collection process by gathering deal-level information of asset-backed securities, including the identity of deal issuers and bookrunners, issuance date, and asset/collateral types (mortgage, credit card, auto loans, bonds, etc.), from the Securities Data Corporation (SDC). We then focus on deals backed by mortgages (i.e., mortgage-backed securities). For all other detailed information on deal, tranche, and collateral characteristics, including cumulative losses (default rates), initial ratings, principal amount, coupon type and rate, deal name and type, maturity, the originator and servicer identities, the geographic distribution of collateral, the loan-to-value (LTV) ratio, and weighted average credit score of the collateral, we manually collect data from Bloomberg. Our sample includes MBS deals originated and issued from 2000 through 2006, and we follow the cumulative losses (percentages of balance write-offs due to default) of these deals/tranches through June of 2012. We obtain ratings from the largest three credit rating agencies—Moody's, S&P, and Fitch—and our final sample includes MBS tranches that are rated by at least one of the agencies at issuance.

1.1 Empirical models

We estimate two sets of models, both as ordinary least squares (OLS) with fixed effects. In the first set, we link the initial yield spread and its interactions with various issuer and market characteristics to *Default rate*, a tranche's cumulative loss rate from the issuance date to June 2012. (In robustness tests, we also model defaults through the end of 2008 and also defaults five years after issuance.) The key explanatory variables are the natural logarithm of the initial yield spread (*Log yield spread*) and its interaction with *AAA* (=1 if at least one rating is AAA), *Hot* (a dummy indicating that a deal is issued in the hot MBS market from 2004 to 2006), *Issuer share* (the lagged MBS market share of the issuer based on the number of deals originated in the previous year), and with *One rating* (a dummy indicating that a tranche is rated by only one credit rating agency at issuance).

To summarize analytically,

$$\begin{aligned}Default\ rate_{i,j,k,t} &= \beta_0 + \beta_1 Log\ yield\ spread_{i,j,t} + \beta_2 Log\ yield\ spread_{i,j,t}\\ &\times AAA_{i,j,t} + \beta_3 Log\ yield\ spread_{i,j,t} \times Hot_t + \beta_4 Log\ yield\ spread_{i,j,t}\end{aligned}$$

[5] In addition, Jiang, Stanford, and Xie (2012) find switching from an investor-pay model to an issuer-pay model leads to ratings inflation in the corporate bond markets, and Stanton and Wallace (2012) find regulation capital arbitrage leads to more inflated ratings in the commercial MBS market.

$$\times \textit{Issuer share}_{k,t-1}+\beta_5 \textit{Log yield spread}_{i,j,t}\times \textit{One rating}_{i,j,t}$$

$$+\textit{Initial rating}\times \textit{Issuance year fixed effects}$$

$$+\textit{Deal, tranche, collateral, and issuer controls}+e_{i,j,k,t}. \tag{1}$$

The data vary by year (t), issuer (k), deal (i), and tranche (j).

In these tests, we include *Initial rating* × *Issuance year* fixed effects, where the initial rating accounts for disagreements between the agencies. For example, we would introduce a separate fixed effect for tranches that receive one BBB rating and one BBB^- rating. One way to think about this approach is first to map the average credit rating into a numerical scale and then to generate a separate indicator variable (i.e., a distinct fixed effect) for each numerical value. By doing so, we impose no specific functional relationship between the outcome and the level of the average credit rating.

We also include separate intercepts for coupon types (floating, fixed, etc.) and deal types given by Bloomberg ("ABS Home," "CMBS," "Private CMO Float," etc.), and we cluster standard errors by issuers.[6] Note that by including the *Initial rating* × *Issuance year* fixed effects, we absorb the direct effect of *Hot*, which has only time variation but no cross-sectional variation; hence, we only report its interaction with *Log yield spread*. Equation (1) completely absorbs the effects of the ratings with fixed effects that vary by issuance year.

In our second set of models, we compare the relative explanatory power of the credit rating versus initial yield spread to test how the information content in each varies with the perceived integrity of the ratings process. To do so, we first map the credit rating into the *Expected default frequency* (*EDF*) based on the past five-year cumulative default data to measure how the ratings ought to predict future defaults. For this analysis, we focus on the years in which the market boomed (since most of the defaults occur for MBS issued in those years), and we focus on the non-AAA market (since we find *Log of yield spread* predicts default only in the non-AAA segment). By replacing ratings fixed effects with the continuous *EDF*, we can compare how our measures of potential compromise to the ratings process impact the incremental explanatory power of both the rating (through the effect of *EDF* on default) and the *Log yield spread.*

Specifically, we estimate the regressions as follows:

$$\textit{Default rate}_{i,j,k,t}=\beta_0+\beta_1 \textit{Log yield spread}_{i,j,t}+\beta_2 \textit{Log yield spread}_{i,j,t}$$

$$\times \textit{Issuer share}_{k,t-1}+\beta_3 \textit{Log yield spread}_{i,j,t}\times \textit{One rating}_{i,j,t}+\beta_4 \textit{EDF}_{i,j,t}$$

$$+\beta_5 \textit{EDF}_{i,j,t}\times \textit{Issuer share}_{k,t-1}+\beta_6 \textit{EDF}_{i,j,t}\times \textit{One rating}_{i,j,t}+\textit{Controls}+e_{i,j,t}. \tag{2}$$

[6] We exclude CMOs with complex prepayment structures, such as interest-only notes (IOs), principal-only notes (POs), or inverse floaters.

We estimate Equation (2) with just *Issuance year* fixed effects in some models, and we also estimate models that absorb the direct effect of the *EDF* with *Initial rating* × *Issuance year*. In these latter instances only the interaction terms are identified. If the integrity of the ratings process is compromised by ratings shopping, then we would expect that *EDF* does not explain future defaults as well for one-rated tranches, whereas *Log of yield spread* predicts default better for such tranches; that is, $\beta_3 > 0$ and $\beta_6 < 0$. Similarly, if large-issuer-sold tranches compromise the ratings process, we would expect $\beta_2 > 0$ and $\beta_5 < 0$.[7]

1.2 Variable construction and summary statistics

Table 1, panel A, provides variable definitions, and panel B reports summary statistics for the overall sample. Panels C–E split the sample by issuance year and the number of ratings.

1.2.1 Dependent variable, yield, and *EDF*. The first two rows of Table 1, panel B, report ex post performance, equal to the percentage of the tranche's original principal balance that had been written off by June 2012 (see Table 1, panel A, for a precise definition of each variable), and the ex ante *Expected default frequency* (*EDF*). The third row reports our measure of ex ante pricing (yield spread). The mean default rate for the MBS tranches in our sample is 19%, and the median is 0%. A large fraction of the tranches are AAA-rated at issuance and most of these have zero losses; in contrast, a small fraction of the subordinated tranches (around 10%) have lost all their balances (i.e., the default rate is 100%). For comparison, we report the *Expected default frequency* (*EDF*). For each tranche, we map its ratings into the *EDF* provided by the S&P Global Structured Finance five-year Cumulative Default Rates ending in December 1999 and then average across all ratings for the tranche. Clearly, default rates prior to the housing boom were much lower than what occurred more recently.

Our key explanatory variable for defaults is the log of the *Initial yield spread*. For a tranche with a floating coupon rate, *Initial yield spread* equals the fixed markup, in basis points, over the reference rate specified at issuance (e.g., the one-month LIBOR rate). For a tranche with a fixed or variable coupon rate (51% of the sample), *Initial yield spread* equals the difference between the initial coupon rate on the tranche and the yield on a Treasury security whose maturity is closest to the tranche's *Average life* (see the definition below). Since most of the securities are priced and sold at par (about 95% of the tranches which we have initial price data have an issue price within 1% of par value), the coupon rate closely approximates the initial yield. The mean for *Initial yield* is 126 bp over the whole sample, with a standard deviation of 83 bp.

7 We address the possibility that interest rate risk and/or prepayment risk could affect the outcome by controlling for the interaction of issuance-year indicators with the *Average Life* of the tranche in all of our regressions.

Table 1
Data description

Panel A: Variable definitions

Default rate: the cumulative loss rate of an MBS tranche (i.e., the percentage of its original principal balance that has been written off due to default) from its issuance date through June 2012. Specifically, we sum the dollar amounts of monthly principal losses over time (from the issuance date through June 2012) and then divide this total loss amount by the tranche's original principal amount to obtain the cumulative percentage loss rate.
Expected default frequency (EDF): the S&P Global Structured Finance 5-year Cumulative Default Rates ending in December 1999 that correspond to the rating of a given tranche.
Initial yield spread: for a tranche with floating coupon, we use the fixed markup over the reference rate specified at issuance (e.g., the one-month LIBOR rate). For a tranche with fixed or variable coupon, we use the difference between the initial coupon rate and the yield of a Treasury whose maturity is closest to the tranche's weighted average maturity.
Issuer share: the number of deals originated by an issuer in the previous year divided by the total number of deals in the same year.
Hot: a dummy that equals one if a tranche is issued between 2004 and 2006.
Issuer rating: the average of the ratings of the issuer itself, at the time of issuance.
Bank-thrift: a dummy that equals one if the issuer is a commercial bank or thrift, and equals zero otherwise.
Same originator servicer: a dummy that equals one if the originator and the servicer of the deal are the same, and equals zero otherwise.
Originator selling to multiple issuers: an indicator equal to one if the originators have sold to more than one issuer during the preceding year.
Initial rating: the average of the ratings a tranche received at issuance, after converting into a numerical value by setting AAA = 1, AA+ = 1.67, AA = 2, AA– = 2.33, and so on.
Level of subordination: the fraction of tranches in the same MBS deal that have a rating the same as or better than a given tranche based on their principal amount.
Rating disagreement: a dummy that equals one if a tranche receives at least two ratings at issuance and the ratings are different from each other, and equals zero otherwise (i.e., if all the ratings are the same or there is only one rating).
Fraction of unrated tranches in a deal: the total principal amount of unrated tranches within a deal divided by the deal principal amount (sum of all tranches' principal amount).
Fraction of excess collateral in a deal: the total amount of all available underlying collateral for a deal minus the deal principal amount (sum of all tranches' principal amount), divided by the deal principal amount.
Principal amount: the principal amount of a tranche at issuance.
Average life: the expected maturity of a tranche's principal repayment, which is the average amount of time (years) that will elapse from the closing date until each dollar of principal is repaid to the investor, typically based on certain standard assumptions about prepayment speeds.
Fraction of collateral in troubled states: the fraction of underlying collateral of each tranche originated in Arizona, California, Florida, or Nevada.
Herfindahl index of collateral: the sum of the squared shares of the collateral within a deal across each of the top five states (with the largest amount of mortgages), with the aggregation of all the other states as the sixth category.
Loan-to-value (LTV) ratio: the weighted average LTV of the underlying collateral for a given tranche at issuance.
Average credit score: the weighted average FICO score of the borrower for a given tranche at issuance.
Fraction of fixed rate mortgages: fraction of underlying collateral in fixed rate mortgages.
Fraction of mortgages with full documentation: fraction of underlying collateral in mortgages with full documentation.
CRA relationship: a dummy that equals one if a tranche is rated by a relationship rating agency at issuance and equals zero otherwise. For a given issuer-agency pair, the agency is defined as the "relationship" agency of the issuer if in the previous year: (1) this agency rated at least 70% of all the deal amounts issued by this issuer and this agency is the "top" agency, that is, it rated more deals sold by this issuer more than the other two agencies, (2) this agency rated at least 60% of all the deals sold by this issuer and it is the "middle" agency (i.e., the second largest agency for this issuer in the previous year) and that the difference between the "middle" and "top" agencies is not larger than 10%, or (3) this agency rated at least 60% of all the deal amounts issued by this issuer and this agency is the "bottom" agency (i.e., the agency with the least market share for this issuer in the previous year) and that the difference between the "middle" and "bottom" agencies is not larger than 10%. For example, if Moody's rated 85% of the deals sold by an issuer, S&P rated 75%, and Fitch rated 58%, then only Moody's and S&P are defined as this particular issuer's "relationship agency" in that year. But if Fitch's share is 65% or higher, then it would be considered a "relationship agency" as well. *CRA relationship* is set to one if the tranche is rated by at least one "relationship" agency.
Number of lagged relationship CRAs: the number of "relationship" CRAs an issuer has in the previous year; can be 0, 1, 2, or 3.
Time to securitize: the weighted number of years between the origination year of the collateral pool and the MBS issuance year. For example, if 90% of a tranche's collateral was originated in 2001, 10% was originated in 2002, and the tranche was issued in 2002, then the weighted time to securitize is 90%*1+10%*0=0.9 years.

(*continued*)

Table 1
Continued

Panel B: Sample statistics for the regression variables

Variable	Mean	SD	N
Dependent variable, Yield and EDF			
Default rate (%)	19.00	37.00	78,995
Expected default freq. (EDF) (%)	1.45	3.99	78,985
Initial yield spread (bp)	125.73	83.06	66,434
Issuer characteristics			
Issuer share (%)	5.00	4.00	78,937
Hot	0.67	0.47	78,995
Issuer rating	2.90	0.93	71,075
Bank or thrift	0.59	0.49	78,995
Same originator and servicer	0.29	0.45	78,995
Missing originator or servicer	0.54	0.50	78,995
CRA relationship	0.85	0.35	74,470
Originator selling to multiple issuers	0.39	0.49	78,995
Missing originator	0.51	0.50	78,995
Number of lagged relationship CRAs	1.42	0.74	78,995
Deal and tranche characteristics			
Principal amount (millions $s)	54.97	122.68	78,988
Initial rating	2.16	1.52	78,995
Level of subordination (%)	92.00	13.00	78,976
Rating disagreement	0.11	0.31	78,995
Number of tranches in deal	23.80	14.30	78,995
Fraction of unrated tranches in deal (%)	4.00	12.00	78,995
Fraction of excess collateral in deal (%)	0.49	2.00	78,777
Average life (in years)	5.73	3.43	69,252
Collateral characteristics			
Fraction of collateral in troubled states (%)	45.32	16.55	71,859
Herfindahl index of collateral	0.34	0.09	71,859
Loan-to-value (LTV) ratio (%)	69.47	15.33	76,419
Average credit score	704	231	45,947
Fraction of fixed rate mortgages (%)	54.00	46.00	71,110
Fraction of mortgages with full doc (%)	39.00	31.00	68,292
Time to securitize (years)	0.23	0.46	71,276

Panel C: Default rates (in %) by the number of initial ratings and issuance year for AAA-rated tranches

Number of initial ratings		Issuance year						
		2000	2001	2002	2003	2004	2005	2006
1	Mean	0.0	0.8	0.1	0.1	0.2	1.2	3.5
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	0.0	8.6	1.2	3.8	4.5	7.7	11.9
	N	160	282	194	706	489	884	507
2	Mean	0.0	0.0	0.0	0.0	0.0	1.2	6.3
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	0.3	1.8	0.1	1.4	1.3	7.2	16.6
	N	1,603	3,147	3,989	4,872	5,542	7,481	6,601
3	Mean	0.0	0.0	0.0	0.0	0.0	1.0	2.8
	Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	SD	0.1	0.2	0.2	0.2	0.1	9.1	11.2
	N	171	344	399	413	770	1,344	2,076

(*continued*)

Table 1
Continued

Panel D: Default rates (in %) by the number of initial ratings and issuance year for non-AAA-rated tranches

Number of initial ratings		Issuance year 2000	2001	2002	2003	2004	2005	2006
1	Mean	9.0	4.9	3.8	5.7	29.6	68.9	86.5
	Median	0.0	0.0	0.0	0.0	1.8	93.9	98.1
	SD	26.7	19.4	16.3	16.8	35.7	40.4	29.3
	N	761	1,054	978	1,666	2,162	3,102	2,203
2	Mean	15.9	10.9	4.9	3.2	9.1	43.1	77.7
	Median	0.0	0.0	0.0	0.0	0.0	16.3	100.0
	SD	34.6	29.2	17.9	13.8	22.6	45.7	39.3
	N	513	796	1,293	2,003	3,199	4,949	6,063
3	Mean	19.7	5.2	3.3	2.0	4.7	35.4	79.7
	Median	0.0	0.0	0.0	0.0	0.0	0.0	100.0
	SD	38.6	18.9	11.1	7.8	13.5	45.0	37.6
	N	79	177	350	490	1,139	1,961	2,025

This table provides data description. Panel A gives variable definitions. Panels B to D report summary statistics of privately issued mortgage-backed securities (MBS) sold between 2000 and 2006 and whose tranches are rated by at least one credit rating agency at issuance.

1.2.2 Issuer characteristics. *Issuer share* equals the number of MBS deals sold by an issuer over the total number of deals sold by all issuers in the previous year (using alternative measures of issuer market share based on the principal amounts gives very similar results). We denote market boom years through a dummy variable, *Hot*, which equals one if a deal is issued between 2004 and 2006, and zero otherwise. We are interested in testing whether the initial yield spreads are more correlated with future losses when the issuers have more market power or when markets boom, so we introduce the interaction variables, *Log yield spread* × *Issuer share* and *Log yield spread* × *Hot.*

Since the value of implicit recourse to investors may increase with issuer reputation, we control for *Issuer rating*, equal to the numerical score for the rating of the issuer at the issuance date (AAA = 1; $AA^{+}=1.67$, AA = 2, $AA^{-}=2.33$, and so on); the mean issuer rating is A. In our tests we also differentiate between issuer types and include an indicator equal to one for banks and thrifts, who face tighter regulatory capital requirements than other MBS issuers, such as finance companies (e.g., GMAC) or investment banks (Bear Stearns, Lehman, etc.).[8] If regulatory arbitrage encourages the regulated banks to securitize their assets more aggressively, then there may be differences in deal structure, collateral quality, pricing, and ex post loss rates. We also construct *Same originator servicer*, an indicator set to one if the originator and the servicer of the tranche are the same firm and zero otherwise. (*Same originator servicer* is also only available for a subset of our data; hence, we

8 Nadauld and Sherlund (2013) show that the five largest broker dealers expanded most aggressively into the subprime mortgage market using securitization during the boom years.

estimate our models with an additional indicator, *Missing originator servicer*, equal to one if the information on originator or servicer is not available.)

CRA relationship is an indicator set to one if a tranche is rated by at least one "relationship" agency of the issuer at issuance, based on the frequency of past ratings from a given agency (see Table 1, panel A, for a complete definition). We also control for the number of past relationships between the issuer and the rating agencies (*Number of lagged relationship CRAs*). To capture the potential effects of relationships between loan originators and issuers, we also control for *Originator selling to multiple issuers*, an indicator set to one if the originator has sold loans to more than one issuer during the prior year (= 1 for 39% of our sample).[9]

1.2.3 Deal and tranche characteristics. The average tranche size (*Principal amount*) in our sample equals about $55 million, with a median of $14 million. *Initial rating*, equal to a numerical score based on the average ratings a tranche received, averages 2.2 (about AA). As our main measure of deal structure, we control for the *Level of subordination* for each tranche, defined as the dollar-weighted fraction of tranches in the same deal that have a rating the same as or better than the given tranche. For example, for a hypothetical $100 million deal with $80 million in the AAA tranche, $10 million in the BBB tranche, and another $10 million in the B tranche, the *Level of subordination* would equal 80% for AAA, 90% for BBB, and 100% for B. This variable increases as the amount of protection for a given tranche by lower rated tranches decreases. We also control for the *Fraction of unrated tranches in a deal* and the *Fraction of excess collateral in a deal*, measured as the ratio of total collateral net of deal principal divided by deal principal.[10] Opp, Opp, and Harris (2013) show theoretically, and Furfine (2014) shows empirically, that more complex deals may lead to greater ratings inflation. Following Furfine (2014), we control for the number of tranches within a deal as a measure of deal complexity.

To capture a given tranche's interest rate risk exposure, we control for its *Average life*, equal to the expected maturity of its principal repayment. In other words, this variable measures the weighted average maturity of the tranche as the average amount of time (in years) that will elapse from the closing date until each dollar of principal is repaid to the investor, typically based on certain standard assumptions about prepayment speed.[11]

[9] As noted in Keys et al. (2010) and Purnanandam (2011), an originator may have diluted incentives to investigate and screen borrowers when selling loans to multiple issuers. We include this variable as a control in our tests, but it does not appear to affect our main results.

[10] Discussion with industry practitioners suggests that issuers of structured finance products do not always use the same rating agency for the entire deal. Consistent with this practice, we find that 50% of the Moody's-rated deals in our sample have at least one tranche (within a deal) rated by another agency. Similarly, 18% (35%) of the deals rated by S&P (Fitch) in our sample have at least one tranche rated by another agency.

[11] Note that this is not the same as duration, which measures the weighted-average time to maturity based on the relative present values of cash flows as weights (see, e.g., Chapter 27 of Saunders and Cornett 2008 for more details).

1.2.4 Collateral. We include a number of control variables to capture characteristics of the underlying collateral. *Fraction of collateral in troubled states* equals the fraction of collateral originated in Arizona, California, Florida, or Nevada. This variable measures the degree of exposure to areas that experienced the highest house price rise leading up to the crisis, followed by the largest drop during the crisis.[12] *Herfindahl index of collateral* measures geographical concentration of the collateral pool, equal to the sum of the squared shares of the collateral within a deal across each of the top five states (with the largest amount of mortgages), with the aggregation of all the other states as the sixth category. This variable controls, admittedly crudely, for the degree of correlation across loans within a given pool. To capture various dimensions of credit risk, we control for the *Loan-to-value (LTV) ratio*, the *Weighted average credit score* (FICO), and the *Fraction of mortgages with full documentation* of the underlying collateral for a given tranche at issuance. Beyond the measure of average life at the tranche level, we also incorporate interest rate risk exposure in the underlying mortgages with the *Fraction of fixed rate mortgages* in the collateral pool.

We also control for a (noisy) measure of the length of time between loan origination and securitization—*Time to securitize*, which averages about 0.24 years (see Table 1, panel A, for a complete definition). This variable helps establish that single-rated tranches are more likely to have been shopped. If a single rating indicates the simplicity of a particular tranche, time to securitize would be lower for them than that for multi-rated tranches; in contrast, if a single rating reflects shopping, time to securitize would be higher.

1.3 Default rates by issuance year and number of ratings

Panels C and D of Table 1 sort tranches into cohorts based on rating, issuance year, and the number of initial ratings. The mean default rate is much greater for tranches issued during the housing market boom of 2004–2006, regardless of how many initial ratings a tranche receives. AAA-rated tranches have very low default rates on average, and the average defaults do not differ much by the number of initial ratings (except for in 2006, where default rates for AAA tranches with two ratings exceeded 6%). In contrast, non-AAA-rated tranches have much higher average default rates (panel D). Moreover, one-rated non-AAA tranches perform much worse than multi-rated tranches, especially for those sold during the market boom. In addition, comparing panels C and D shows that while one-rated tranches only constitute a small proportion of the AAA market across all years, they carry much more weight in the non-AAA market. For example, in 2005, one-rated tranches comprise only 9.1% of the AAA market [= 884 / (884 + 7,481 + 1,334)] but 31.0% of the non-AAA market

[12] The importance of this variable may be obvious only in hindsight, although some analysts were concerned about overheated regional markets in real time. All of our key results are robust to the exclusion of this variable.

Table 2
Rating and default characteristics by initial rating categories and the number of initial ratings

Panel A: Full sample (2000–2006)

	Fraction of 1-rated (1)	Fraction disagreement (2)	Loss of 1-rated (3)	Loss of 2-rated (4)	Loss of 3-rated (5)	EDF (6)
AAA	7.41	2.80	1.00	1.92	2.16	0.00
AA	23.29	35.44	19.80	34.87	25.45	0.02
A	25.09	36.33	30.45	40.56	39.58	0.32
BBB	26.77	28.65	41.58	45.15	47.74	2.38
BB and worse	62.07	11.60	57.37	45.18	60.91	11.77
Panel B: Hot-period sample (2004–2006)						
AAA	6.97	4.06	1.52	3.18	2.81	0.00
AA	17.76	39.91	33.91	43.05	29.50	0.02
A	19.98	42.86	52.20	52.80	47.58	0.36
BBB	23.59	33.96	64.83	59.86	59.87	2.46
BB and worse	62.66	13.57	78.42	58.67	68.60	11.22

This table reports the rating and default characteristics by initial rating categories and the number of initial ratings. We classify each MBS tranche based on the best rating it has at issuance and report the average rating and default characteristics in each category. Panel A uses the whole sample, which includes all privately labeled MBS deals issued between 2000 and 2006 and rated by at least one credit rating agency at issuance. Panel B uses rated MBS deals that are issued from 2004 to 2006. For each rating category, "Fraction of 1-rated" is the percentage of tranches that got only one rating at issuance, "Fraction Disagreement" is the percentage of two- or three-rated tranches whose initial ratings disagree with each other, and "Loss of X-rated" (X=1, 2, and 3, respectively) is the average default rate over tranches that got X ratings at issuance. "EDF" is the average expected default frequency over all tranches for a rating notch. Every item in the table is expressed in percentages.

[= 3,102 / (3,102 + 4,949 + 1,961)], and this pattern holds true for most of the other years in our sample.

Table 2 reports further rating and default characteristics sorted by initial rating categories (based on the best rating a tranche receives at issuance) and the number of initial ratings. The vast majority of AAA tranches (near 93%) are rated by two or three rating agencies; in contrast, non-AAA tranches have considerably higher fractions of one-rated tranches. More than 60% of the tranches with initial ratings of BB and worse are rated by only one rating agency at issuance, suggesting that lower-rated tranches outside the AAA market are more likely to have been shopped (i.e., their inferior ratings were hidden from the market).

The second column in the table, based only on those tranches with two or three ratings, shows an inverted U-shaped pattern of disagreement with regard to the initial rating categories. Both the AAA tranches and tranches with "BB and worse" have a very low level of rating disagreement. Less than 3% of AAA tranches have different initial ratings from different agencies. This may be due, in part, to the fact that these tranches with very high or low credit quality are easier to rate. Tranches with intermediate credit quality, and thus middle initial ratings, may be harder to evaluate and require more discretion from the agencies, thus leading to a much higher rating disagreement level. The evidence here for AAA-rated tranches is consistent with the findings of Griffin, Nickerson and Tang (2013), who argue that "ratings catering" leads to a low level of disagreement for AAA-rated tranches in their sample of collateralized debt obligations (CDOs).

Columns 4–6 report the average default rates for tranches with one, two, and three initial ratings, respectively. While the average default rates for one-rated AAA tranches are much smaller than for two- or three-rated AAA tranches, this pattern reverses outside the AAA market during the boom years. As we go down the rating notches, the average default rates for one-rated tranches tend to match or exceed the loss rates for two- or three-rated tranches. This pattern is stronger in panel B of Table 2, which only focuses on the market booming period from 2004 to 2006. For tranches whose best initial ratings are "BBB" or worse, their average default rates are higher if these tranches only have one initial rating. Column 7 reports the *Expected default frequency* (*EDF*) by rating bins based on the five-year cumulative defaults observed up to 1999. Clearly, these EDFs are much lower across the whole ratings distribution, compared to what occurred during the end of the housing boom.

These univariate comparisons suggest that while one-rated tranches on average perform better than multiple-rated tranches for higher initial rating categories (such as the AAA), potentially consistent with "ratings catering," one-rated tranches tend to perform worse than multiple-rated ones for lower initial rating categories, indicating a "shopping" effect in the non-AAA market, where inferior initial ratings have been dropped by the issuers. Figure 1 makes the above comparisons clear by plotting the ex post default rates against the credit rating for one-, two-, and three-rated tranches. We report the loss rates for tranches receiving nondisagreeing ratings during the hot market period, where potential ratings shopping incentives are the strongest. One-rated tranches have a much higher average default rate than multiple-rated tranches in the non-AAA market; the pattern is strongest below the investment grade.

These simple summary statistics indicate that the credit quality of tranches issued in the market booming period and those with only one rating is lower than those issued from 2000–2003 and those with multiple ratings, especially in the non-AAA market.[13]

1.4 What correlates with single-rated tranches?

Table 3, panel A, describes differences between some predetermined issuer and collateral characteristics conditional on rating level (AAA versus non-AAA) and one-rated versus multi-rated. In Table 3, panel B, we estimate probit models (and report marginal effects), for which the dependent variable equals one for single-rated tranches and zero otherwise. We include only variables that are

[13] To address the concern that our main measure of rating shopping, that is, the dummy for one-rated tranches, might have picked up the fundamentally different nature of those MBS deals without any AAA tranches, we tried excluding such deals (less than 1% of the sample) from our empirical analysis and obtained qualitatively similar results.

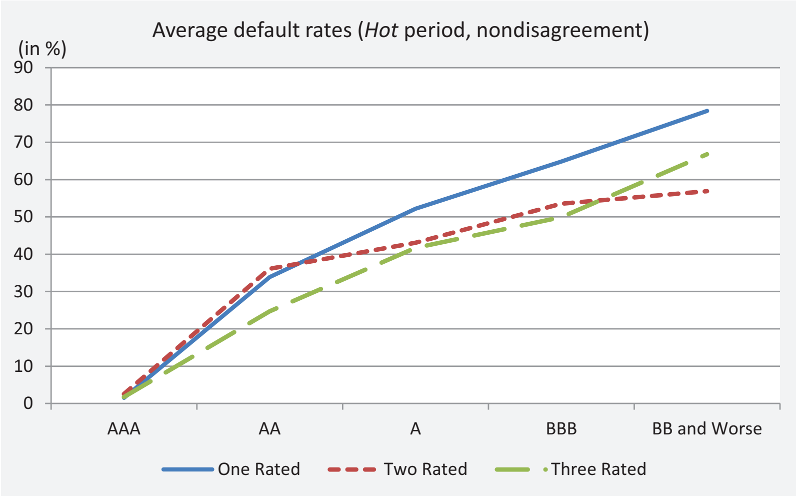

Figure 1
The average default rates for the different rating categories, by the number of initial ratings
This figure shows the average default rates for tranches with different rating categories by their number of initial ratings (nondisagreement sample)

predetermined relative to the process of building the tranche structure, so we omit deal and tranche characteristics, such as the number of tranches, the level of subordination, ratings disagreement, and the rating itself.

Both the univariate comparisons (panel A) and the probit regressions (panel B) support our interpretation that a single rating is indicative of shopping. Larger issuers are more likely to sell one-rated tranches, consistent with the idea that they have substantial bargaining power relative to rating agencies (and thus shop more). Moreover, and even more striking, an increase in the average time to securitization increases the likelihood of having one rating. This result seems hard to understand unless one-rated tranches have been shopped. Otherwise, one would expect just the opposite, as dealing with a single rating agency would reduce the time needed to put together a deal. But if one-rated tranches are more likely to be shopped, these cases involve a preliminary rating received from multiple agencies, which increases the time needed to complete the deal.

Table 3 also suggests that both credit risk and interest rate risk characteristics are correlated with having a single rating. Tranches with longer average lives are more likely to have one rating, although this effect is driven by non-AAA tranches (panel A). This shows that it is important to control for interest rate risk in our main tests (Equations (1) and (2)). However, we show in our robustness tests that our key result remains nearly unchanged regardless of whether or not we control for measures of interest-rate risk exposure.

For credit risk, we find, if anything, that safer deals are more likely to have one rating, as *LTV* enters the probit models with a negative and

Table 3
A description of one-rated MBS tranches

Panel A: Univariate comparisons of one-rated and multi-rated tranches

	One-rated		Multi-rated		Diff
AAA-rated	Mean	SD	Mean	SD	*t*-stat
Issuer share (%)	5.00	3.00	6.00	4.00	6.23
Number of lagged relationship CRAs	1.24	0.77	1.41	0.73	12.69
Principal amount (millions $)	56.88	128.45	95.43	159.13	13.38
Average life (in years)	4.80	4.09	5.09	3.85	3.68
Time to securitize (in years)	0.30	0.72	0.23	0.48	8.34
Loan-to-value (LTV) ratio (%)	63.80	15.45	67.82	13.33	16.03
Non-AAA-rated					
Issuer share (%)	6.00	4.00	4.00	4.00	38.16
Number of lagged relationship CRAs	1.31	0.74	1.53	0.73	27.31
Principal amount (millions $)	5.46	8.68	15.71	29.34	37.38
Average life (in years)	8.22	2.54	6.05	2.25	69.42
Time to securitize (in years)	0.25	0.58	0.24	0.49	1.40
Loan-to-value (LTV) ratio (%)	65.66	14.22	74.60	17.23	48.59

Panel B: Probit model, dependent variable = 1 for one-rated MBS tranches

	All years (1)	*Hot* 2004–2006 (2)	Non-*Hot* 2000–2003 (3)
Hot market indicator	0.0012	–	–
	(0.08)	–	–
Issuer share	0.3021**	0.1887	−0.0420
	(2.17)	(1.15)	(−0.19)
Log of principal	−0.0399***	−0.0397***	−0.0442***
	(−13.80)	(−10.68)	(−10.72)
Log of average life	0.0923***	0.0814***	0.1074***
	(8.65)	(8.60)	(7.96)
Fra. of colla. in troubled states	−0.0009**	−0.0006	−0.0018**
	(−2.44)	(−1.07)	(−2.53)
Herfindahl index of collateral	0.0644	0.0491	0.1756*
	(0.86)	(0.58)	(1.92)
Same originator and servicer	0.0341*	0.0366**	0.0381
	(1.84)	(2.12)	(1.34)
Missing originator or servicer	0.0306	0.0048	0.1927***
	(1.40)	(0.30)	(3.23)
Issuer rating	0.0057	0.0095	0.0143
	(0.78)	(1.25)	(1.19)
Bank of thrift	−0.0275	0.0065	−0.1225***
	(−1.43)	(0.34)	(−6.35)
Loan-to-value (LTV) ratio	−0.0023***	−0.0014***	−0.0037***
	(−7.02)	(−3.61)	(−5.49)
Average credit score	0.0000	0.0000	−0.0007
	(0.77)	(1.44)	(−1.37)
Missing credit score	−0.0125	−0.0019	−0.5027
	(−0.82)	(−0.11)	(−1.47)
Frac. of fixed rate	−0.0605***	−0.0643***	−0.0216
	(−3.90)	(−3.72)	(−0.70)
Frac. of mortgages with full doc	−0.0401**	−0.0240	−0.0683**
	(−1.96)	(−0.84)	(−1.98)
Originator selling to multiple issuers	−0.0194	0.0101	−0.1779***
	(−0.90)	(0.38)	(−3.24)
Missing originator	−0.0073	0.0009	−0.0207
	(−0.50)	(0.04)	(−0.54)
Num. of lagged relationship CRAs	−0.0330***	−0.0361***	−0.0286**
	(−3.37)	(−3.08)	(−2.46)
Time to securitize	0.0212***	0.0341***	−0.0081
	(2.64)	(3.55)	(−0.51)
Observations	50,692	35,695	14,997
Pseudo R-squared	0.201	0.195	0.233

This table examines which tranches are likely to be one rated. Panel A compares the key characteristics of one-rated and multi-rated tranches across AAA and non-AAA tranches. Panel B reports probit regressions (marginal effects) of an indicator equal to one for MBS tranche with one rating on collateral and issuer characteristics. Variables are defined in Table 1. Each regression includes separate intercepts for coupon types (floating, fixed, etc.) and deal types given by Bloomberg (“ABS Home,” “CMBS,” “Private CMO Float,” etc.). Standard errors are clustered by issuers. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

significant coefficient and is lower on average for one-rated tranches in both AAA and non-AAA segments (panel A). We also find that issuers with more *Lagged relationship CRAs* have one rating less often, which probably picks up persistence at the issuer level in the number of ratings paid for on their typical deal.

2. Regression Results

In this section we report our main results, the estimates of Equations (1) and (2). As we have argued, absent agency problems, the rating should reflect credit risk to a great extent; hence, initial yield spreads should not explain future losses once we adequately control for the rating and other characteristics. If, instead, ratings are inaccurate (either because of undue bargaining power by large issuers or because issuers have engaged in shopping), and if investors produce independent information beyond that contained in the rating, then the initial yield spread will be correlated with future (ex post) losses.

2.1 Do yields explain future losses?

In Table 4, we regress the ex post defaults on the natural logarithm of initial yield spread (*Log yield spread*) and other characteristics of the tranches, deals, the issuer, and the market. In these regressions we control for the rating nonparametrically and allow its relationship to default to vary over time by including a separate fixed effect for each unique level of the average credit rating in each cohort year (Equation (1)). We also include dummy variables for coupon types (floating, fixed, etc.) and deal types given by Bloomberg ("ABS Home," "CMBS," "private CMO Float," etc.), which are not reported. We cluster the standard errors of the coefficients by issuers across all models.

2.1.1 Results. Credit and interest rate risks, both of which may affect pricing, raise a broad challenge in identifying and interpreting the *Log yield spread* coefficients. To control for credit risk information (possibly) not captured by the rating, we include measures of both borrower leverage (*LTV*) and borrower quality (*Average credit score*), as well as a measure of the amount of collateral from troubled states. Beyond that, in robustness tests (panel B) we report models that fully absorb credit risk variations with collateral-level fixed effects. We have identification in these models because multiple tranches (of the same deal) with different ratings and yields receive cash flows from a common set of underlying mortgages.

The probit model in Table 3 shows that one-rated tranches have higher *Average life*, suggesting that its correlation with losses may reflect prepayment rather than differences in credit quality. For example, if borrowers prepay faster for one-rated tranches and if borrowers who leave the pool are more creditworthy, then the remaining ones might be more likely to default. To capture this possibility, in all of our models we absorb variation in prepayment

Table 4
A regression of MBS default rates on initial yields, 2000–2006

Panel A: Cumulative default as of 2012

	(1)	(2)	(3)	(4)	(5)
Log yield spread	0.0579***	0.0511***	0.0454***	0.0439***	0.0384***
	(7.44)	(7.13)	(5.65)	(6.08)	(4.99)
Log yield spread * AAA	−0.0708***	−0.0707***	−0.0708***	−0.0657***	−0.0658***
	(−7.57)	(−7.64)	(−7.63)	(−7.56)	(−7.56)
Log yield spread * Hot	–	0.0094***	0.0105***	0.0102***	0.0113***
	–	(2.99)	(3.64)	(3.10)	(3.70)
Log yield spread * Issuer share	–	–	0.0861*	–	0.0835*
	–	–	(1.85)	–	(1.75)
Log yield spread * One rating	–	–	–	0.0247**	0.0245**
	–	–	–	(2.08)	(2.07)
Issuer share	−0.0343	−0.0356	−0.4282*	−0.0374	−0.4184*
	(−0.44)	(−0.46)	(−1.97)	(−0.48)	(−1.90)
One rating	0.0260*	0.0260*	0.0264*	−0.0916	−0.0904
	(1.90)	(1.91)	(1.95)	(−1.54)	(−1.52)
Two rating	0.0036	0.0037	0.0043	0.0041	0.0048
	(0.34)	(0.35)	(0.42)	(0.39)	(0.47)
Log of principal	−0.0059**	−0.0058**	−0.0059**	−0.0058**	−0.0059**
	(−2.30)	(−2.28)	(−2.29)	(−2.27)	(−2.27)
Fra. of colla. in troubled states	0.0017***	0.0017***	0.0017***	0.0017***	0.0017***
	(6.39)	(6.40)	(6.37)	(6.42)	(6.39)
Herfindahl index of collateral	−0.1842***	−0.1834***	−0.1837***	−0.1820***	−0.1822***
	(−5.23)	(−5.23)	(−5.31)	(−5.23)	(−5.31)
Same originator and servicer	−0.0089	−0.0091	−0.0088	−0.0089	−0.0086
	(−0.81)	(−0.84)	(−0.82)	(−0.83)	(−0.80)
Missing originator or servicer	−0.0101	−0.0101	−0.0104	−0.0101	−0.0104
	(−0.46)	(−0.46)	(−0.48)	(−0.46)	(−0.48)
Issuer rating	0.0099*	0.0099*	0.0100*	0.0099*	0.0100*
	(1.69)	(1.69)	(1.70)	(1.70)	(1.71)
Level of subordination	0.0681	0.0603	0.0672	0.0664	0.0730
	(0.78)	(0.71)	(0.82)	(0.77)	(0.88)
CRA relationship	0.0076	0.0077	0.0075	0.0075	0.0073
	(0.90)	(0.91)	(0.88)	(0.88)	(0.85)
Rating disagreement	0.0403*	0.0396*	0.0394*	0.0403*	0.0401*
	(2.01)	(1.97)	(1.97)	(1.99)	(1.99)
Log of num tranches in deal	−0.0116	−0.0111	−0.0109	−0.0111	−0.0109
	(−1.41)	(−1.34)	(−1.32)	(−1.35)	(−1.34)
Bank thrift	−0.0071	−0.0072	−0.0068	−0.0069	−0.0066
	(−0.63)	(−0.63)	(−0.60)	(−0.62)	(−0.58)
Loan-to-value (LTV) ratio	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***
	(2.96)	(2.95)	(2.95)	(2.95)	(2.95)
Average credit score	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.60)	(0.58)	(0.57)	(0.59)	(0.58)
Missing credit score	0.0053	0.0055	0.0052	0.0055	0.0052
	(0.55)	(0.57)	(0.54)	(0.57)	(0.54)
Frac. of fixed rate	−0.0319**	−0.0329**	−0.0329**	−0.0331**	−0.0331**
	(−2.63)	(−2.68)	(−2.67)	(−2.70)	(−2.68)
Frac. of mortgages with full doc	−0.0556***	−0.0552***	−0.0548***	−0.0549***	−0.0545***
	(−4.67)	(−4.67)	(−4.59)	(−4.68)	(−4.61)
Frac. of unrated	0.0542	0.0473	0.0552	0.0522	0.0598
	(0.57)	(0.51)	(0.62)	(0.55)	(0.66)
Frac. of excess collateral	−0.2853***	−0.2774***	−0.2770***	−0.2783***	−0.2780***
	(−2.82)	(−2.76)	(−2.72)	(−2.75)	(−2.72)
Originator selling to multiple issuers	0.0094	0.0096	0.0092	0.0094	0.0090
	(1.09)	(1.12)	(1.08)	(1.10)	(1.05)
Missing originator	0.0114	0.0113	0.0117	0.0112	0.0116
	(0.54)	(0.53)	(0.55)	(0.53)	(0.55)
Time to securitize	−0.0623***	−0.0623***	−0.0622***	−0.0625***	−0.0623***
	(−6.95)	(−6.94)	(−6.90)	(−6.98)	(−6.95)
Rating * Cohort year	yes	yes	yes	yes	yes
Average life * Cohort year	yes	yes	yes	yes	yes
Observations	46,002	46,002	46,002	46,002	46,002
R-squared	0.745	0.745	0.745	0.745	0.745
F-test for var. involving yield	30.03	20.36	21.99	16.57	18.48
p-value for F-test	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

(*continued*)

Table 4
Continued

Panel B: Robustness tests

	Losses that include foregone interest	Drop control variables	Include only floating-rate tranches	Default five years after issuance	Add collateral fixed effects		Alternative definition of ratings fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log yield spread	0.0305**	0.0319**	0.0424***	0.0326***	0.0422***	0.0375***	0.0414***
	(2.40)	(2.03)	(3.12)	(3.64)	(5.01)	(3.79)	(5.52)
Log yield spread * AAA	−0.0330**	−0.0595***	−0.0734***	−0.0504***	−0.0458***	−0.0459***	−0.0685***
	(−2.30)	(−3.20)	(−3.88)	(−5.43)	(−5.02)	(−5.03)	(−7.41)
Log yield spread * Hot	0.0143**	0.0121*	0.0129*	0.0162***	−0.0051	−0.0042	0.0109***
	(2.37)	(1.93)	(1.88)	(5.59)	(−1.52)	(−1.15)	(3.80)
Log yield spread * Issuer share	−0.0952	0.1797**	−0.0013	0.0710	–	0.0681	0.0682
	(−1.61)	(2.45)	(−0.01)	(1.50)	–	(0.83)	(1.40)
Log yield spread * One rating	0.0334**	0.0239**	0.0391**	0.0309***	0.0206**	0.0203**	0.0245*
	(2.35)	(2.50)	(2.25)	(3.04)	(2.10)	(2.07)	(1.96)
Issuer share	0.4853	−0.6776**	−0.2762	−0.5964**	–	–	−0.3419
	(1.58)	(−1.98)	(−0.65)	(−2.33)	–	–	(−1.57)
One rating	−0.1550**	−0.0920**	−0.1341*	−0.1434***	−0.0204	−0.0191	−0.0830
	(−2.13)	(−2.16)	(−1.86)	(−2.99)	(−0.39)	(−0.37)	(−1.23)
Two rating	0.0060	0.0076	0.0057	0.0026	0.0437***	0.0439***	0.0041
	(0.75)	(1.05)	(0.50)	(0.25)	(2.79)	(2.80)	(0.43)
Control variables included	yes	no	yes	yes	yes	yes	yes
Rating * Cohort year FE	yes	yes	yes	yes	yes	yes	yes
Average life * Cohort year	yes	no	yes	yes	yes	yes	yes
Collateral FE	no	no	no	no	yes	yes	no
Observations	5,791	46,002	22,067	46,000	46,002	46,002	46,002
R-squared	0.745	0.728	0.735	0.713	0.854	0.854	0.739
F-test for var. involving yield	4.932	4.51	5.868	32.27	9.226	7.536	16.05
p-value for F-test	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

This table reports OLS regressions of MBS default rates on the natural logarithm of initial yield spread (*Log yield spread spread*) and other tranche-level, deal-level, and issuer-level characteristics. "AAA" is a dummy that equals one if the best rating is AAA or equivalent, and zero otherwise. "Rating * Cohort Year" is the full set of dummies that indicate each average initial rating category in each cohort (issuance) year. "Average Life * Cohort Year" is the full set of interactions between a tranche's "Log Average Life" and each cohort (issuance) year. The average initial rating category refers to each level of the average ratings a given tranche received at issuance, after we convert the individual ratings into a numerical value by setting AAA = 1, AA+ = 1.67, AA = 2, AA− = 2.33, and so on and then take the arithmetic averages of all the ratings this tranche receives. Other variables are defined in Table 1. Each regression includes separate intercepts for coupon types (floating, fixed, etc.) and deal types given by Bloomberg ("ABS Home," "CMBS," "Private CMO Float," etc.). In panel B, we only report coefficients of interest, and all of the other variables are included as in panel A. Standard errors are clustered by issuers. t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

as best as we can by interacting issuance year indicators with *Log average life*. This is not a perfect control, but it allows the effects of maturity and prepayments to vary with interest-rate risk dynamics, since its slope coefficient can differ by year. This approach captures the idea that fixed rate mortgages would be more likely to be repaid during periods of falling interest rates. The most salient point for our paper is that absorbing these effects has little impact on the main result, as we show in the robustness tests that the magnitude of the coefficient of interest is insensitive to dropping these controls entirely.[14] To the extent that fixed rate mortgages are subject more to interest-rate risk than floating ones, we have also controlled for the fraction of fixed rate mortgages in the collateral pool in all regressions.

Table 4, panel A, reports our baseline results. Tranches with a single rating have much higher default rates than multiple-rated tranches, conditional on ratings. The coefficient on *One Rating* in column (1) suggests that conditional on ratings and other observables, the average default rate for a tranche with only one initial rating is 2.6 percentage points higher than a similar tranche with two or three initial ratings. Given that the average default rate in our sample is 19 percent, this represents a substantial difference.

Log yield spread is strongly predictive of MBS default rates, but only for non-AAA tranches; in fact, the sum of the coefficients on *Log yield spread* and *Log yield spread * AAA* signs negatively. We also find the predictive power of *Log yield spread* strengthens when we interact it with the *Hot* indicator (panel A, column 2). Consistently across these models, we find a high degree of joint significance for variables involving the *Log yield spread* (see the F-statistics at the bottom of the columns).

Columns (3)–(5) show that the information content in yields increases as the integrity of the rating process degrades: yields matter most when the issuer is large and when the tranche receives one rating. The coefficients of both *Log yield spread * Issuer share* and *Log yield spread * One rating* enter significantly. Their magnitudes are similar, regardless of whether we add them one at a time (Columns 3 and 4) or together (Column 5). To assess magnitudes, we consider increasing the *Log yield spread* by 0.4, equal to one standard deviation within a ratings bin. That is, 0.4 equals the root of the mean squared error of the residual from regressing the *Log yield spread* on the full set of *Initial rating* $\times$ *Issuance year* fixed effects (in the non-AAA segment). Magnitudes are substantial: the coefficient on *Log yield spread * One rating* from Column (5) indicates that for tranches with only one initial rating (in the *non-AAA* market during *Hot* years and at the average level of *Issuer Share*), moving the log yield spread by

[14] Another caveat is that yields reflect both the probability of default and loss given default, and ratings focus typically on the former. Thus, incremental explanatory power for yields could be generated by variation in loss given default. We try to correct for this discrepancy by controlling for collateral characteristics (e.g., collateral types and geographical concentration) that might be correlated with loss given default, and we show that our results are not sensitive to whether or not these variables are included in the model (see Table 4, panel B).

0.4 would be associated with a default rate that is 3.1 percentage points higher [= 0.4 × (0.0384 + 0.0113 + 0.0835 × 0.05 + 0.0245) × 100].

Other control variables relate to future default rates as expected. For example, tranche size (*Log of principal*) is negatively associated with future losses, indicating that larger tranches are in general safer. Tranches with a greater fraction of their underlying mortgages originated from "troubled" states (AZ, CA, FL, and NV) have significantly higher future losses. Interestingly, better-diversified tranches, as measured by a lower cross-state HHI, have higher cumulative losses. This suggests, consistent with Coval, Jurek, and Stafford (2009), that market yields did not fully capture the systematic risk embedded in well-diversified MBS (proxied by the HHI), at least based on ex post default experience. If the market did price this risk correctly, the default rate would fall with diversification (after controlling for yield): comparing two MBS with the same yield, the better diversified one should default less because a greater portion of its yield compensates for systematic risk. *Issuer rating* has a significantly positive effect on default rates, suggesting that declines in an issuer's credit standing (i.e., a higher "rating score" in our regressions) decrease the issuer's value of implicit recourse (Gorton and Souleles 2007).

Rating disagreement in the initial ratings is associated with higher future default rates, indicating that risky tranches may be harder to evaluate and may induce more diverse opinions from the agencies. (That said, most of any disagreement effect is absorbed by the average ratings fixed effect since we build these effects from the average rating; for example, we would include a separate fixed effect for a two-rated tranche with one AAA rating and one AA$^+$ and interact this with the issuance-year effects.) In contrast to Furfine (2014), our proxy for deal complexity (*Log number of tranches*) is not related to future losses. We find no evidence that a relationship based on prior interactions between issuers and rating agencies is correlated with greater future losses. Sensibly, the *Loan-to-value* (*LTV*) *ratio* of the underlying collateral is positively related to its future losses, and collateral with more full documentation and deals with more excess collateral default less.

2.1.2 Robustness tests. In panel B of Table 4, we report seven robustness tests on the main results from panel A. In column (1), we estimate the model with an alternative loss variable that accounts for lost interest payments (available for a subset of the dataset). In Column (2), we estimate a simple model with just the fixed effects and our variables of interest (i.e., no other controls). In Column (3), we report the model with just floating rate tranches (about 50% of the full sample), where measurement error in the *Log yield spread* is less of a concern. In Column (4), we change the dependent variable to the cumulative losses five years after the year in which the deal was sold.[15] In Columns (5) and

[15] We have also estimated the model on default through 2008, with similar signs and significance but somewhat smaller magnitudes since defaults would not have fully materialized by that point.

(6), we drop the collateral control variables and replace them by saturating the model with same-collateral fixed effects; this strategy fully absorbs unobserved heterogeneity in either credit or interest rate risk characteristics of the pool.

Last, in Column (7) we change how we build ratings fixed effects for one-rated tranches. We have argued that having only one rating indicates that the unreported rating(s) would have been lower than the reported one. This indicates that the stronger correlation between *Log yield spread* and subsequent default could reflect errors in the way we control for the rating, rather than more information content in the yield itself. To rule out this alternative hypothesis, we explicitly account for a possible bias in the ratings of these tranches as follows: we lower the (supposedly omitted) rating of each one-rated tranche by one notch. For example, we would assign a one-rated tranche issued in 2005 with a BBB rating to the same ratings category (in terms of the fixed effect included in the test) as a two-rated tranche issued that year with a BBB (the observed) and a BBB^- (the omitted) ratings configuration. Similarly, we would treat a tranche with one A rating the same as a tranche with a ratings combination of an A and an A^-.

In all robustness tests, *Log yield spread* interacts positively and significantly with *One rating*. When we use the same sample as in panel A, this interaction varies from 0.0203 to 0.0309, very close to the coefficient estimate in panel A (0.0245, in Column 5), whereas it rises somewhat when we look at cumulative losses including foregone interest (to 0.0334) or use only floating-rate tranches (to 0.0391). The *AAA* indicator consistently interacts negatively in all models. *Hot* interacts positively and significantly in five of seven models; this variable loses power, however, in the model that is saturated with collateral fixed effects. The *Log yield spread* * *Issuer share* signs positively in four of six cases, but is less robust statistically.

2.2 Focusing on the hot years: 2004–2006

Table 5 reports the same set of models (Equation (1)) split by time. We report the model pooled across 2000–2003 (*non-Hot* years) and 2004–2006 (*Hot* years), always with Ratings * Cohort fixed effects. The predictive power of yields for future losses is much stronger during the latter portion of the sample, when the markets were at their peak. The interaction of *Log yield spread* with *One rating*, for example, is nearly zero in 2000–2003, but rises to 0.05 in the *Hot* years. Similarly, the *Issuer size* interaction appears to be driven by these later years. For the *Ho*t period (Column 4), a one-sigma increase in *Log yield spread* within a rating bin (a change of 0.4) for one-rated, non-AAA tranches would predict a 4.0% increase in default [$= 0.4 \times (0.0413 + 0.1775 \times 0.05 + 0.0496) \times 100$].

In Table 6, we split the sample further, separating the data into AAA (panel A) versus non-AAA rated tranches (panel B). Panel C then subdivides the non-AAA sample into each broad rating category (AA, A, BBB, and BB or worse). In the AAA market, *Log yield spread* has significant predictive power for future

Table 5
A regression of MBS default rates on initial yields

	2000–2003 (1)	2000–2003 (2)	2004–2006 (3)	2004–2006 (4)
Log yield spread	0.0111***	0.0111***	0.0509***	0.0413***
	(3.14)	(3.13)	(5.36)	(3.77)
Log yield spread * AAA	−0.0103**	−0.0103**	−0.0720***	−0.0722***
	(−2.73)	(−2.71)	(−6.75)	(−6.76)
Log yield spread * Issuer share	–	0.0010	–	0.1775***
	–	(0.05)	–	(3.01)
Log yield spread * One rating	0.0033	0.0033	0.0498**	0.0496**
	(0.56)	(0.56)	(2.58)	(2.60)
Issuer share	−0.0026	−0.0073	−0.0114	−0.7939***
	(−0.10)	(−0.08)	(−0.10)	(−3.37)
One rating	−0.0150	−0.0150	−0.1920**	−0.1903**
	(−0.53)	(−0.53)	(−2.10)	(−2.10)
Two rating	0.0016	0.0016	0.0040	0.0054
	(1.04)	(1.05)	(0.36)	(0.50)
Rating * Cohort year effects	yes	yes	yes	yes
Average life * Cohort year effects	yes	yes	yes	yes
Observations	12,125	12,125	33,877	33,877
R-squared	0.146	0.146	0.729	0.729
F-test for var. involving yield	6.368	5.220	17.12	22.56
p-value for F-test	0.002	0.003	<0.001	<0.001

This table reports OLS regressions of the MBS default rates on the natural logarithm of initial yield spread (*Log yield spread*) and other tranche-level, deal-level, and issuer-level characteristics, as in Table 4. We report coefficients of interest; see Table 4, panel A, for full set of control variables, whose coefficients are not reported below. Standard errors are clustered by issuers. t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

losses, especially for tranches sold by large (Columns 2 and 3). But we find no evidence that one-rated tranches have higher loss rates (Column 1, coefficient on *One rating*) or that yields matter more for one-rated tranches (Column 3, coefficient on *Log yield spread * One rating*).

Patterns in the non-AAA segment differ sharply from the AAA segment (panel B). For these tranches, the power of initial yield spreads to explain default is the strongest for one-rated tranches and for tranches sold by large issuers. For non-AAA, one-rated tranches, varying the *Log of yield spread* by one standard deviation within ratings categories (a change of 0.4 in Column 3) would be associated with an increase in default of 4.7 percentage points [$= 0.4 \times (-0.0038 + 0.6255 \times 0.05 + 0.0900) \times 100$]. When we subdivide the sample rating bin by bin (panel C), we see that the interaction between *Log of yield spread* with *Issuer share* is strong in the higher-rated bins (AA and A), whereas the interaction with *One rating* is strong in the lower-rated bins (A, BBB, and BB). But the positive interaction between *Log of yield* spread and *One rating* is quite robust during the boom period. We find it in three of the four non-AAA ratings-bin subsamples.

The results in the low-rated tranches are in sharp contrast to the AAA market: most investors in the non-AAA market are not required to obtain two or more ratings, so issuers have more freedom to drop pessimistic ratings. Thus, shopping lets issuers conceal bad news. Consistent with this notion, more than 60% of the below-investment-grade tranches have just one rating (recall

Table 2). Therefore, ratings for one-rated non-AAA tranches are likely to have an inflationary bias, as issuers choose not to purchase and report pessimistic ratings. Perceiving such ratings shopping behavior, the market performs the most due diligence for one-rated, non-AAA tranches, thus making the initial yield spread the most informative about future losses (conditional on *Initial rating* $\times$ *Issuance year* fixed effects).

2.3 Horse race: Ratings (EDFs) versus yield

In our last set of tests, we compare the relative strength of ratings versus yields in predicting default, focusing on the boom years and the non-AAA segment. We capture ratings with a continuous measure of expected default

Table 6
A regression of MBS default rates on initial yields, *Hot* period (2004–2006), AAA versus non-AAA

Panel A: AAA Sample

	(1)	(2)	(3)
Log yield spread	0.0078**	0.0026	0.0026
	(2.35)	(0.41)	(0.41)
Log yield spread * Issuer share	–	0.0952*	0.0952*
	–	(1.78)	(1.79)
Log yield spread * One rating	–	–	−0.0022
	–	–	(−0.47)
Issuer share	0.1360**	−0.2707	−0.2709
	(2.52)	(−1.13)	(−1.13)
One rating	−0.0012	−0.0003	0.0094
	(−0.14)	(−0.03)	(0.50)
Two rating	0.0054	0.0064	0.0064
	(0.76)	(0.89)	(0.88)
Rating * Cohort year	yes	yes	yes
Average life * Cohort year	yes	yes	yes
Observations	18,671	18,671	18,671
R-squared	0.283	0.283	0.283
F-test for var. involving yield	5.519	11.09	7.534
p-value for F-test	0.025	< 0.001	0.001

Panel B: Non-AAA sample

	(1)	(2)	(3)
Log yield spread	0.0569***	0.0230	−0.0038
	(4.91)	(1.21)	(−0.17)
Log yield spread * Issuer share	–	0.6287**	0.6255**
	–	(2.49)	(2.67)
Log yield spread * One rating	–	–	0.0900***
	–	–	(3.71)
Issuer share	−0.0847	−2.9710**	−2.9766**
	(−0.36)	(−2.53)	(−2.71)
One rating	0.0502	0.0507	−0.3761***
	(1.57)	(1.60)	(−3.21)
Two rating	0.0092	0.0115	0.0139
	(0.29)	(0.37)	(0.45)
Rating * Cohort year	yes	yes	yes
Average life * Cohort year	yes	yes	yes
Observations	15,206	15,206	15,206
R-squared	0.627	0.628	0.630
F-test for var. involving yield	24.11	16.50	18.03
p-value for F-test	< 0.001	< 0.001	< 0.001

(*continued*)

Table 6
Continued

Panel C: Non-AAA-rated, bin by bin

	AA-rated (1)	A-rated (2)	BBB-rated (3)	BB or worse (4)
Log yield spread	0.0002	−0.0165	0.0538	0.0790
	(0.01)	(−0.54)	(1.24)	(0.57)
Log yield spread * Issuer share	1.7712***	0.9326***	−0.5996	−1.7959
	(6.30)	(3.60)	(−1.07)	(−1.00)
Log yield spread * One rating	0.0231	0.1084***	0.0918**	0.1860**
	(0.58)	(3.49)	(2.75)	(2.66)
Issuer share	−7.6335***	−4.3385***	2.9773	9.0396
	(−5.88)	(−3.30)	(1.08)	(0.95)
One rating	−0.1033	−0.4701***	−0.3181*	−0.9820**
	(−0.61)	(−3.00)	(−1.79)	(−2.62)
Two rating	0.0302	−0.0304	0.0460	0.0358
	(0.92)	(−0.91)	(1.33)	(0.52)
Rating * Cohort year	yes	yes	yes	yes
Average life * Cohort year	yes	yes	yes	yes
Observations	5,449	4,821	4,625	237
R-squared	0.608	0.637	0.624	0.685
F-test for var. involving yield	43.92	12.61	5.379	2.517
p-value for F-test	<0.001	<0.001	0.004	0.086

This table reports OLS regressions of the MBS default rates on the natural logarithm of initial yield spread (*Log yield spread*) and other tranche-level, deal-level, and issuer-level characteristics, as in Table 4. We report coefficients of interest; see Table 4, panel A, for full set of control variables, whose coefficients are not reported below. Standard errors are clustered by issuers. t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

using *Expected default frequency* (*EDF*) by converting each letter-grade rating into the *EDF* for that letter grade, based on the S&P Global Structured Finance five-year Cumulative Default Rate through the end of 1999 (the last year before our sample begins).[16] We estimate both the direct effect of *EDF* on ex post default (in models without *Initial rating* × *Issuance year* fixed effects), and its interactions with issuer market share and the one-rating indicator, and compare them with the effects of *Log of yield spread*.

Panel A of Table 7 reports the results for all non-AAA tranches issued between 2004 and 2006. Columns 1–3 omit the ratings fixed effects, and Columns 4–6 include these effects and thus absorb the direct effect of *EDF*. The coefficients on the *Log yield spread* interaction terms are consistent, regardless of whether or not we include the ratings fixed effects (compare Columns 3 and 6). The marginal effect of the yield is consistently greater where concern about the integrity of the ratings process is most likely to be compromised, that is, when issuers are large or when one rating is reported (positive interactions). Further, we find that the opposite is true for *EDF*: wherever concern about the integrity of the ratings process is most likely to be compromised, the effect of *EDF* is reduced (negative interactions).

16 We have also used Moody's corporate bond EDF, that is, the five-year cumulative default rates for annual corporate bond cohorts formed 1970 through 1997, and obtain results similar to those reported here.

Table 7
A regression of MBS default rates on initial yields for non-AAA tranches in *Hot* period only, with EDF

Panel A: Non-AAA only

	Issuance-year fixed effects			Initial rating x Issuance-year fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Log yield spread	0.0662***	0.0066	−0.0248	0.0450***	−0.0082	−0.0393*
	(5.84)	(0.32)	(−1.04)	(4.29)	(−0.42)	(−1.77)
Log yield spread * Issuer share	–	1.1023***	1.0974***	–	0.9689***	0.9826***
	–	(4.36)	(4.40)	–	(4.21)	(4.64)
Log yield spread * One rating	–	–	0.1033***	–	–	0.1045***
	–	–	(4.09)	–	–	(4.44)
EDF	0.0261***	0.0338***	0.0441***	–	–	–
	(5.45)	(4.89)	(5.01)	–	–	–
EDF * Issuer share	–	−0.1417	−0.1320	–	−0.3099***	−0.3227***
	–	(−1.29)	(−1.25)	–	(−4.42)	(−4.82)
EDF * One rating	–	–	−0.0187**	–	–	−0.0053
	–	–	(−2.45)	–	–	(−0.74)
Issuance year fixed effects	yes	yes	yes	no	no	no
Initial rating x Issuance year fixed effects	no	no	no	yes	yes	yes
Average life x Cohort year	yes	yes	yes	yes	yes	yes
Observations	16,104	16,104	16,104	16,104	16,104	16,104
R-squared	0.560	0.562	0.564	0.630	0.632	0.634
F-test for var. involving yield	34.12	49.43	34.54	18.44	16.29	18.89
p-value for F-test	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Panel B: Predicted percentage-point increase in default rates (using coefficients from Column 3, panel A)

	2% increase in *EDF* (1)	0.4 increase *Log yield* (2)	Fraction of increase from the change in *EDF* (1)/[(1)+(2)]
(1) Small issuer, multirated	8.8	−1.0	112%
(2) Small issuer, one-rated	5.1	3.1	62%
(3) Large issuer, multi-rated	6.2	3.4	65%
(4) Large issuer, one-rated	2.4	7.6	25%

This table reports OLS regressions of the MBS default rates on the natural logarithm of initial yield spread (*Log yield spread*), together with the interaction terms involving the *Expected default frequency* (EDF) for non-AAA tranches issued in the hot period (from 2004 to 2006). All variables are defined in the previous tables. We include the same set of control variables, but we only report the coefficients of interest. Panel B gives the percentage-point increase in default rates for various groups of tranches sorted by number of ratings and issuer market share, using coefficients from Column 3, panel A. Standard errors are clustered by issuers. t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

By including the direct effect of *EDF*, we can compare the power to explain future defaults for ratings versus that of the market yield. Table 7, panel B, summarizes the results of this exercise. We compare the change in predicted losses for one-rated tranches sold by small issuers (with market share close to zero), one-rated tranches sold by large issuers (with 10% market share), multi-rated tranches sold by small issuers, and multi-rated tranches sold by large issuers. For each configuration, we compute the predicted increase in default based on the coefficients in Column 3 of panel A. We simulate what would occur by increasing the *EDF* by 2 percentage points, equivalent to moving the rating from A to BBB (recall Table 2) and comparing this to what the same model predicts by moving the *Log yield spread* up by 0.4, equivalent to the standard deviation (the root of the mean squared error) of the residual from regressing the *Log yield spread* on the full set of *Initial rating* × *Issuance year* fixed effects (in the non-AAA segment). For example, in the last row of Table 7, panel B, the change in predicted defaults from a 2-percentage-point increase in *EDF* is computed as follows: 2.4% = (0.0441–0.1320 × 10%–0.0187) ×2 × 100%. The change in predicted defaults from a 0.4 increase in the *Log of yield spread* is computed as follows: 7.6% = (–0.0248 + 1.0974 × 10% + 0.1033) × 0.4 × 100%.

For each configuration, we compute an increase in default of 7 to 10 percentage points (the sum of Columns 1 and 2). This increase is about the same as what we observe moving from A to BBB in the raw data (recall Table 2). For tranches sold by small issuers with more than one rating, the rating change (*EDF*) accounts for all (> 100%) of the total increase in predicted defaults due to both yield and EDF increases (row 1). Yet *EDF* has little ability to explain the increase in default for tranches sold by large issuers with one rating, accounting for only 25% of the increase (row 4). For these cases, a one-standard-deviation increase in the yield predicts a change in default that is twice as large as a change in the credit rating from A to BBB.

3. Conclusions

With growing evidence revealing problems in the rating process, researchers, practitioners, and regulators have recently focused on "rating shopping," whereby issuers only purchase and report the most favorable rating(s) after receiving preliminary opinions from multiple agencies. In this paper, we study the effects of shopping in the MBS markets by linking cumulative losses on tranches to the yield spreads at issuance. We argue that if the market questions the integrity of the ratings process, then initial yield spreads ought to be more correlated with ex post performance (conditional on the rating).

With a large sample of MBS sold between 2000 and 2006, we find that default rates rise dramatically for tranches sold during the market boom (2004–2006) and that tranches with a single rating (below AAA) have higher losses than those with multiple ratings. In the non-AAA segment, initial yield spreads predict future losses, and they do so more strongly for single-rated tranches than for multi-rated ones. These results suggest that these single-rated tranches have been "shopped" so that pessimistic ratings never reach the market. In the AAA market, by contrast, yields are at best weakly related to future performance, and the result is similar for one-rated and multi-rated tranches. In this segment, investors were seemingly naïve, relying too heavily on ratings.

Overall, our results show that shopping adversely affected the quality of ratings in the MBS market. Investors in the riskier segment of the market (below AAA) at least partially priced this risk into yields. That said, many of the lower-rated tranches were bought not by final investors but by other financial intermediaries, who in turn repackaged them as CDOs. According to the Financial Crisis Inquiry Report (2011), "Almost 80% of these CDO tranches would be rated triple-A, despite the fact that they generally comprised the lower-rated tranches of mortgage backed securities (page 127)". Thus, while sophisticated intermediaries seemed to understand the presence of deficiencies in credit ratings, most final investors in the CDO market may have failed to price deals commensurate with their true risk.

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