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MORTGAGE-BACKED SECURITIES AND THE FINANCIAL CRISIS OF 2008:
A POST MORTEM

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ABSTRACT

We examine the payoff performance, up to the end of 2013, of non-agency residential mortgage-backed securities (RMBS), issued up to 2008. We have created a new and detailed data set on the universe of non-agency residential mortgage backed securities, per carefully assembling source data from Bloomberg and other sources. We compare these payoffs to their ex-ante ratings as well as other characteristics. We establish seven facts. First, the bulk of these securities was rated AAA. Second, AAA securities did ok: on average, their total cumulated losses up to 2013 are 2.3 percent. Third, the subprime AAA-rated segment did particularly well. Fourth, later vintages did worse than earlier vintages, except for subprime AAA securities. Fifth, the bulk of the losses were concentrated on a small share of all securities. Sixth, the misrating for AAA securities was modest. Seventh, controlling for a home price bust, a home price boom was good for the repayment on these securities. Together, these facts provide challenge the conventional narrative, that improper ratings of RMBS were a major factor in the financial crisis of 2008.

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A data appendix is available at http://www.nber.org/data-appendix/w24509

1 Introduction

post mortem: an examination of a dead body to determine the cause of death[1]

Gradually, the deep financial crisis of 2008 is in the rearview mirror. With that, standard narratives have emerged, which will inform and influence policy choices and public perception in the future for a long time to come. For that reason, it is all the more important to examine these narratives with the distance of time and available data, as many of these narratives were created in the heat of the moment.

One such standard narrative has it that the financial meltdown of 2008 was caused by an overextension of mortgages to weak borrowers, repackaged and then sold to willing lenders drawn in by faulty risk ratings for these mortgage back securities. To many, mortgage backed securities and rating agencies became the key villains of that financial crisis. In particular, rating agencies were blamed for assigning the coveted AAA rating to many securities, which did not deserve it, particularly in the subprime segment of the market, and that these ratings then lead to substantial losses for institutional investors, who needed to invest in safe assets and who mistakenly put their trust in these misguided ratings.

In this paper, we re-examine this narrative. We seek to address two questions in particular. First, were these mortgage backed securities bad investments? Second, were the ratings wrong? We answer these questions, using a new and detailed data set on the universe of non-agency residential mortgage backed securities (RMBS), obtained by devoting considerable work to carefully assembling data from Bloomberg and other sources. This data set allows us to examine the actual repayment stream and losses on principal on these securities up to 2014, and thus with a considerable distance since the crisis events. In essence, we provide a post-mortem on a market that many believe to have died in 2008. We find that the conventional narrative needs substantial rewriting: the ratings and the losses were not nearly as bad as this narrative would lead one to believe.

Specifically, we calculate the ex-post realized losses as well as ex-post realized return on investing on par in these mortgage backed securities, under various assumptions of the losses for the remaining life time of the securities. We compare these realized returns to their ratings in 2008 and their promised loss distributions, according to tables available from the rating agencies. We shall investigate, whether ratings were a sufficient statistic (to the degree that a discretized rating can be) or whether they were, essentially, just "noise", given information already available to market participants at the time of investing such as ratings of borrowers.

[1]The market for non-agency residential mortgage backed securities pretty much died with the financial crisis: new issuance slowed to a trickle. Thus, the title.

We establish seven facts. First, the bulk of these securities was rated AAA. Second, AAA securities did ok: on average, their total cumulated losses up to 2013 are 2.3 percent. Third, the subprime AAA-rated segment did particularly well. Fourth, later vintages did worse than earlier vintages, except for subprime AAA securities. Fifth, the bulk of the losses were concentrated on a small share of all securities. Sixth, the misrating for AAA securities was modest. Seventh, controlling for a home price bust, a home price boom was good for the repayment on these securities.

Table 10 presents more detailed results for these returns, depending on the market segment and assumptions regarding terminal value: these results are presented in greater detail in subsection 5. The most important result here may be that various categories of AAA securities provided an internal rate of return of about 2.44% to 3.31% on average, depending on the assumptions regarding their terminal value. The yield on 10-year treasuries in 2008 was between 3 and 4 percent: the difference is surely smaller than what the standard crisis narrative seems to suggest. It mattered quite a bit, whether the mortgages were fixed rate or floating rate. We do not deny that losses occurred and that these were magnitudes larger than those that should be expected of AAA securities. However, we suggest that these data on the realized returns on AAA RMBS present an interesting challenge to researchers, seeking to place these securities at the center of the storm, tossing world-wide financial markets into the abyss.

Losses were considerably larger on securities with ratings other than AAA. We examine them in considerable detail. Some were practically wiped out as a group, despite rather stellar non-AAA ratings ex ante. The total market share of these securities was below 14 percent of the market for non-agency RMBS, however. Moreover, we calculate that the the total losses on all non-agency RMBS amounted to less than 350 billion dollars: less than 2.5 percent of US GDP or less than half a percent annualized over that period, and quite a bit less than the amount devoted to the 2009 American Recovery and Reinvestment Act or "stimulus" package. We suggest that it is an interesting challenge to craft a theory of a world-wide recession, triggered by the these losses.

We should emphasize that we only examine non-agency residential mortgage backed securities. Agency-backed securities were backed implicitly by the tax payer and explicitly by programs of the Federal Reserve Bank. Therefore their role in the crisis was largely a matter of policy, and investors did not expect losses on investments in these securities to be large. By contrast, the non-agency portion really was the "wild west" of that market, and provides the most stringent restrictions for challenging the conventional narrative. Also, we do not investigate higher layers of leveraging and repackaging, such as, say, AAA-rated collateralized debt securities, backed by a basket of lower-rated mortgage-backed securities. Note that losses here are just redistributing the losses of the original RMBS. There are a variety of other securities that got their share of blame. None have received quite the attention of non-agency residential mortgage backed securities, though, which are the focus here.

The paper proceeds as follows. Section 2 provides a discussion of the related literature. Section 3 discusses our unique and novel data set, and how we assembled it. Subsection 4 contains our analysis. Subsection 4.1 examines the ratings, in particular their relationship and their predictive value for future losses. Subsection 4.2 examines the depth, probability and distribution of losses. In subsection 4.6 we explore errors in rating from an ex post perspective, and the degree of rating reversals, where securities with higher ratings experienced larger losses than those with lower ones. Subsection 5 examines the resulting annualized returns on an investment at par value, under a range of assumptions on the terminal value. Section 6 concludes.

2 Related Literature

Our paper is mainly related to the extensive literature that studies securitization, housing markets, and their role in the unfolding of the financial crisis of 2008. Our paper is closely related to papers that give more importance to non-sumbrime segments of the market as key determinants of the crisis. Adelino et al. (2016) and Adelino et al. (2017), provide evidence that middle-class borrowers with above-subprime credit scores increased their delinquencies in mortgages during the crisis and were key in understanding the crisis. In addition, Albanesi et al. (2017) explain that credit growth between 2001 and 2007 and mortgage delinquencies during the crisis were driven by mid to high credit score borrowers, while debt issued to high risk borrowers was virtually constant. Moreover, the prime segment disproportionately defaulted on their mortgages, mainly because of the role played by real estate investors who maximized leverage motivated by the prospect of capital gains. These results are consistent with our results that Alt-A securities and Prime securities, especially in the AAA-rated group, did by many measures worse than AAA subprime securities. In line with these papers, our results cast doubt on the so-called "subprime view" of crisis.

Our paper is also related to the literature that explores losses and returns on mortgage-backed securities during the crisis. Partly due to data being more readily available, partly due to the fact that unconventional monetary policy made them part of the Fed's balance sheet, and partly due to their importance as a fraction of the MBS market, most studies have focused on the agency mortgage-backed securities. Diep et al. (2017) focus on the cross-section of agency MBS returns, how prepayment risk is priced, and how risk premia changes over time. Boyarchenko et al. (2017) study variation on agency MBS spreads over time and across securities, finding that cross-sectional return patterns are explained by pre-payment risk while the time series variation is mostly accounted for a factor that depends on MBS supply and credit risk. Our paper, in contrast, focuses on the returns of the non-agency market and links them to credit risk, which is absent in agency MBS. Unlike for the agency MBS, our return computations cannot be based on trading prices, and traditional empirical asset pricing analysis is impossible. Despite these limitations, our paper makes the contribution of providing measures of returns and how they relate to potentially risk-priced characteristics. As pointed out by Vickery and Wright (2013), there are key institutional characteristics of the agency MBS market that makes its liquidity higher, and while issuances and activity in the non-agency segment of the market remained robust, they declined in the non-agency market. The results of our study suggest points at some features of the non-agency market that have determined this decline. A salient one is the narrative that subprime-AAA securities had large losses, which further diminishes the liquidity and appetite for the non-agency market. A set of papers, including Barnett-Hart (2009), Beltran et al. (2013), Cordell et al. (2012), has set its attention on the non-cash segment of the market, documenting losses on CDOs and more derivative-like structures. There seems to be agreement on the large losses suffered by CDOs and how rating agencies may have failed to assess the risk in their AAA tranches. Our paper shows, however, that losses on CDOs are not coming from widespread losses on MBS, and that the extent of misratings of agency AAA-rated MBS is not comparable to that of CDOs.

Another strand of the literature studies the role and pertinence of credit ratings. A key issue of ratings is what they mean for investors and society as a whole. Our paper, does show that ratings had useful information about the fundamentals of securities, but our results, suggest that credit ratings were not sufficient statistics for non-agency MBS losses (in line with Ashcraft et al. (2011)). Some researchers have proposed that AAA securities are treated like money, and that the AAA-subprime crisis is more of a run on money-like instruments than a default story. [2] For example, McDonald and Paulson (2015) document this interpretation as a possibility for the AIG crisis. However, Chernenko et al. (2014) examine micro-data of insurance companies and mutual funds holdings of fixed income securities and show that not all investors treated all AAA-rated securitizations the same way, and that some of them understood that they could represent different underlying risks. This means that even though the AAA money-like interpretation is a possibility, it may not be the entire story. The fact that the AAA rating is an insufficient statistic is reinforced by Stanton and Wallace (2011) who document that prices for the AAA ABX.HE index CDS during the crisis were inconsistent with any reasonable

[2] We thank Arvind Krishnamurthy for pointing this as a possible explanation of some of our results

assumption for mortgage default rates, and that these price changes are only weakly correlated with observed changes in the credit performance of the underlying loans in the index.

Finally, there is a literature that explores how securitization helped to create conditions for the crisis to happen and how securitization standards are related to the so-called mortgage crisis. Examples of this literature include Keys et al. (2009), Keys et al. (2010) and Keys et al. (2012). These papers build on substantial evidence that securitization contributed to bad lending by reducing incentives of lenders to carefully screen borrowers, and explore different aspects of the securitization process that could have been affected by this moral hazard problem. They find that regulation had the effect of increasing moral hazard as more regulated banks faced less market discipline. They also find that securitization did lower screening standards: loans with higher FICO scores tend to have higher probabilities of default and a higher probability of being securitized. Finally they show that certain loans, particularly those with higher FICO scores also tend to be easier to securitize and they tend to spend less time on a lender's balance sheet. The fact that loans with higher FICO scores had bigger probabilities of defaults is in line with our findings that subprime-AAA securities seemed to have loss rates that were lower than those of AAA-AtlA securities. The fact that loss rates and probabilities of default for AAA-subprime did not increase in the run-up to the crisis as they did for prime and Alt-A securities, further supports the channels stressed by this literature on how the process of securitization could have influenced the crisis. Unlike these papers, our paper sheds some light on the extent to which credit ratings, another aspect of the securitization process, was a sufficient statistic for the risk involved in investing in mortgage-backed securities.

3 The data

We seek to investigate the market for residential non-agency mortgage-backed securities. These securities are excluded from guarantees or insurance by the government agencies "Fannie Mae" (FNMA), "Freddie Mac" (FHLMC) or "Ginnie Mae" (GNMA) due to certain characteristics, such as "jumbo loans" exceeding the limit of, say, \$ 333,700 in 2004, loans on second properties such as vacation homes, insufficient documentation or borrowers with credit history problems. At the end of 2003, non-agency MBS/ABS had an outstanding amount of \$ 842 billion , constituting 20% of the entire market for MBS, with agency-backed securities constituting the other 80%.

For our investigation, a major challenge was to obtain a suitable data set for these securities. The market is characterized by considerable decentralization. While the appointed trustees of a deal are responsible for providing investors with detailed information about the performance of the loans underlying the securities every month, there is no centralized repository that collects and organizes the data[3]. In terms of prices, many of these securities do not trade very often, and when they do so the transactions are over-the-counter. This makes it impossible to obtain a suitable time series of transaction prices for individual deals[4].

As there was no readily available, organized data source, we constructed the main data ourselves. We start from the Mortgage Market Statistical Annual 2013 Edition by Inside Mortgage Finance[5]. This publication in Volume II, Table A, Non-Agency MBS Activity, contains a complete list of the RMBS deals, completed over the years 2006-2012. For each deal, the name, the original issuer, the original amount and a few other characteristics are listed. There are a total of 2824 such deals. However, information such as cash flow or losses is not provided here. For our further data base construction, we obtain data from Bloomberg.

For each deal listed by the Mortgage Market Statistical Annual 2013 edition, we search for that deal on Bloomberg. The matching sometimes required a bit of a search, and we managed to find nearly 96 percent of the original list, by principal amount. Once we found the appropriate deal entry, we look for all deals that have similar names going forward and going back in time. Bloomberg lists the deal manager for the original deal. We then also search for all mortgage backed securities from this deal manager from 1987 onwards. Proceeding in that manner, we find a total of 8615 deals, going back to 1987 rather than just 2006, as in the Statistical Annual. In this way we hope to have minimized the number of deals that we may be leaving out. Each deal generates approximately 17 separate securities or bonds on average, usually with different ratings, for a total of 143,232 securities, each of which we seek to track. Their total principal amount is 5,842 billion dollars. Further details are in Table 1. Table 2 provides an overview of the data we obtained for each security.

[Insert Table 1 about here]

[Insert Table 2 about here]

In this manner, we obtain as complete a universe of RMBS securities emerging from these deals, as seems possible, as well as information about their ratings and monthly cash flow and losses. We downloaded the various pieces of information, security by security, and assembled it into a spread sheet, readable by MATLAB for further analysis. The process took several months to complete, largely due to the download restrictions of Bloomberg. In order to understand our data base construction further, appendix C provides a sample of the information available from

[3] Some companies including Corelogic and Blackbox Logic collect and sell information and analytic tools to market participants

[4] Now the Financial Regulatory Authority (FINRA) provides some summary statistics on prices and volume of daily transactions.

[5] Information about this source can be found here `http://www.insidemortgagefinance.com/books/`

the Statistical Annual as well as from Bloomberg, how to read the available information and some details on how we constructed our data base. The on-line database appendix contains a detailed step by step description of how we built our data. A replication kit is available from the authors for those that seek to replicate our analysis.

Table TA1 in the technical appendix compares the deals in our final database with those in the Statistical Annual. Panel A of that table provides evidence that our database contains about 94% of the deals and about 96% of the issued amount across different types of securities over the 2006-2012 period, which is the available period in the 2013 edition of the Statistical Annual. The fraction covered by our data is about the same across different market segments. Panel B shows the coverage by market segment over time to show that not only the coverage is high overall, but also that it is high consistently over time. The high matching rate for this time period, and the procedure that we followed to search for securities, give us confidence that our conclusions will not follow from having a selected sample.

We complemented this main data set with data on RMBS price indices as well as house prices. For RMBS prices we obtain the ABX.HE indexes from Markit[6] , which are built to represent CDS transactions on Subprime RMBS issued in 2006 and 2007 for different credit rating levels. Finally, we use publicly available house price data at the state level from Zillow to build some of our control variables.[7]

3.1 Database description

Our constructed database contains information for more than 143 thousand RMBS, which were issued between 1987 and 2013 and are part of about 8,500 securitization deals. Table 1 shows the issuance activity over time. The table shows the boom in activity in terms of deals, bonds, market participants (issuers), and deal size from the early 2000s through 2007, and the corresponding collapse after 2008. Most of the deals after 2008 correspond to resecuritizations.

About 99% of the securities in our data, which represent 97% of the dollar principal amount, are private-label (non-agency), non-government backed,[8] non-CDO securities. We will limit our analysis to these securities throughout the paper.

The collected information can be grouped into groups. The first group is the cash flow time series information. This constitutes the bulk of our data. Given downloading limits imposed by Bloomberg, we had to spend several months downloading this information chunk by chunk. For each security we observe the interest payments, principal payments, outstanding balance,

[6]Information about these indexes and how to purchase the data is available here `https://www.markit.com/Product/ABX`

[7]This data can be downloaded at `http://www.zillow.com/research/data/`

[8]The government backed securities include agency securities and also non-agency securities whose underlying mortgages are backed by the Federal Housing Administration (FHA) and the U.S department of Veterans Affairs (VA)

the coupon rate and the losses each month after issuance. The second group of variables allows to identify the security and describe some of its characteristics. These include the Cusip ID, deal names, deal managers names, dates of issuance, coupon type and frequency, maturity date, type of tranche, notional amounts, as well as the credit rating assigned by up to 5 different credit rating agencies upon issuance. A third group of variables is related to the collateral of the securities, i.e. the underlying mortgages. These include information on the composition of the mortgages by type of rates (adjustable rates vs fixed rate mortgages), by type of occupancy (vacation home, family home, etc), by purpose of the mortgage (equity take out, refinance, purchase), or by geography (at the state level). This group of variables also includes information commonly used to assess the risk of pools of mortgages. We observe moments of the distribution of the credit scores, loan size, and loan to value ratios across the mortgage loans underlying a deal. A final group of variables include variables that can help us classify securities (for example agency vs non-agency, residential vs non-residential MBS) and commonly used metrics in mortgages backed security analysis such as weighted average maturity (WAM), weighted average coupon (WAC), and weighted average life (WAL). In the on-line appendix we list and describe all the variables in the raw data.

[Insert Table 1 about here]

3.2 Classifying Securities into Market Segments

The most common classification used in the market and one that has determined the narratives of the crisis yields three main categories of MBS: Sub-prime, Alt-A, and Prime (or jumbo)[9]. This classification is available from the Mortgage Market Statistical Annual and it is based on the classification of the bulk of the underlying loans into the same three categories. In general, an RMBS predominantly backed by subprime loans will be classified as a Subprime RMBS.

Prime non-agency mortgages are jumbo loans that are not qualified for agency guarantees because of their size. Alt-A or Alternative A are loans in the middle of the credit spectrum, with missing documentation or with other characteristics that make them ineligible for agency securitization. Subprime loans are loans further down the credit quality spectrum, to the point that they too are ineligible for agency backing. In practice, the classification of a security (and the underlying loans) was the result of the market practice in the securitization business and not a contractual characteristic of the security. This means that we do not have an official field that provides the classification, and therefore we perform the classification ourselves. The

[9]There are other classifications that we largely ignore. As one example, there is the Scratch & Dent category. These are loans of borrowers with the lowest FICO scores, which sometimes could have been originated outside the underwriting guidelines. These will generally fall under the sub-prime category

classification criteria often used by banks involved the FICO score, loan-to-value ratios (LTV), loan size, and the documentation supporting the loan, with the FICO score being the main characteristic.

In order to classify the securities in our database, we used the fact that the Mortgage Market Statistical Annual provides a classification for the deals issued after 2005 to learn from our data what FICO score (or other characteristic) would provide an appropriate classification criteria. Figure 1 compares that classification for deals issued after 2005 to the mean FICO scores, loan sizes and LTVs available from Bloomberg. Clearly the FICO score is the key distinguishing characteristic, although size also provides information. Figure TA1 as well as related figures in the technical appendix further supports this claim. Given the distributions of the FICO scores statistics in Figure 1 and Figure TA1, we found cutoffs that we then used to classify each security in the database as Prime, Alt-A, and Subprime.

[Insert Figure 1 about here]

4 Seven Facts

4.1 Fact 1: the bulk of these securities was rated AAA

Table TA2 in the technical appendix describes the credit rating activity in our database based on the assignment of a rating upon issuance. More than 62% of the securities (which represent 85% by value of principal) had at least 2 ratings. For our analysis, we summarize the ratings by the different agencies into a single index, as follows. We abstract from the rating qualifiers "-" and "+". So for example a BBB+ for us is a BBB and an A- is an A. This should not be too problematic since an A- should be closer to an A than to a BBB. Whenever a security has 2 or more ratings from different agencies we average the rating. For instance, if agency 1 rates it as AAA, and rating agency 2 as AA, and rating agency 3 as AAA, the bond will be AAA.[10] For the case of two agencies, one rating a bond as AAA and one as AA, we solved the tie upwards, so the bond would be AAA. These discrepancies are not common in the data.

With table 3, we can now document our ***first fact***: **The great majority of non-agency RMBS securities were assigned a AAA rating upon issuance**. The table shows the total principal amount in billions of Dollars and in terms of percent of the total by rating category. Almost 87% of the principal amounts had the highest rating of AAA. Most of the other rated securities were investment grade securities (BBB or higher). Those rated below constituted

[10]This clearly requires a mapping of the different ratings across agencies. We used the mapping provided by the Bank of International Settlements, which is available here `http://www.bis.org/bcbs/qis/qisrating.htm`

less than 2% of the market by principal value. Table TA3 in the technical appendix contains additional detail.

[Insert Table 3 about here]

4.2 Fact 2: AAA securities did ok.

A loss occurs, when a scheduled payment is not made or when there is a complete default on the remaining principal and stream of payments. The losses that we observe, are the realized losses as defined in the oficial prospectus of the MBS. The losses are reported in the monthly reports that deal managers send to investors. The losses from defaulted loans first reduce excess cash flow, then reduce the level of overcollaterilization, and to the extent they exceed the amount of excess interest and overcollateralization following distributions of principal on the payment date, are allocated to reduce the principal amount according to the level of subordination of the bond in the capital structure of the deal. We observe the time series of the losses suffered month by month by each of the securities in our data. This allows us to calculate the cumulative losses at different points in time and study the differences across ratings, vintages, and market segments. The results presented here are weighted by the original principal amounts of the RMBS's. The technical appendix complements this with unweighted results.

[Insert Table 4 about here]

Table 4 provides a breakdown of the cumulated losses until December 2013 by ratings subcategory. The first column essentially repeats the first column of table 3. The numbers are now somewhat smaller, since the securities involved in table 3 are all the non-agency RMBS of our database, this is, all securities issued between 1987 and 2013[11], whereas the calculations for table 4 only used securities issued up to 2008. From here onwards all the results only use securities issued through 2008. Table TA4 in the technical appendix provides additional detail. We have also plotted the losses over time and according to rating subcategories: these plots are provided in the technical appendix as figures TA2 and TA3. The summary of these plots is that losses started to occur only after the end of 2007 and the onset of the financial crisis, and that they look like having mostly converged until the end of December 2013, except perhaps for the losses on the AAA securities. As of December 2013, AAA securities taken together still had $341 billion of cushion coming from lower-rated bonds. Given that all the losses over 6 years from 2008 to 2013 (both included) did not reach this amount and given the recovery of

[11] Including the information up to 2013 for the activity of agencies is to provide a complete description of our data. Given the fall in securitization activity after 2008, the numbers change a little bit, but the messages do not.

the US economy, we We therefore conjecture with some confidence, that the final loss numbers will be somewhat, but not substantially higher, once one calculates them in, say, 2040.

Table 4 documents our ***second fact***: **AAA securities did ok: on average, their total cumulated losses up to 2013 are 2.3 percent.** This also emerges from section 5 below, where we examine the realized returns in greater detail. Losses for other rating segments were substantially higher, e.g. reaching above 50 percent for non-investment grade bonds. Here, it may be good to bear in mind our first fact, however, that the bulk of securities was rated AAA, as is evident once again from table4. The overall cumulated losses on all RMBS until December 2013 amounted to 6.5 percent. It was the AAA segment in particular that drew the most attention in the discussions regarding ratings. Nobody should be utterly surprised to incur losses on non-investment grade bonds, for example. We therefore focus our discussion here on the AAA segment, while not denying the substantial losses in the other segments.

Cumulative losses of 2.2% of principal on AAA-rated securities surely is a large amount, given that rating. Such losses after six years may be expected for, say, BBB securities [12], and not for AAA securities. AAA securities are meant to be safe securities, and losses should be extremely unlikely. From that vantage point, an average 2.2% loss rate is certainly anything but "ok". We have chosen this label not so much in comparison to what one ought to expect from a AAA-rated security, but rather in comparison to the conventional narrative regarding the financial crisis, which would lead one to believe that these losses had been far larger. Ultimately, of course, different judgements can be rendered from different vantage points: our main goal here is to simply summarize the facts.

4.3 Fact 3: the subprime AAA-rated segment did particularly well.

[Insert Table 5 about here]

We break down the analysis by market segment defined by loan type (Prime, Alt-A, and Subprime). Table 5 shows the results and documents the ***third fact***: **the subprime AAA-rated RMBS did particularly well.** AAA-rated Subprime Mortgage Backed Securities were the safest securities among the non-agency RMBS market. As of December 2013 the principal-weighted loss rates AAA-rated subprime securities were on average 0.42% We do not deny that even the seemingly small loss of 0.42% should be considered large for any given AAA security. Nonetheless, we consider this to be a surprising fact given the conventional narrative for the causes of the financial crisis and its assignment of the considerable blame to the subprime market and its mortgage-backed securities. An example of this narrative is provided by Gelman

[12]see the table available from Moody's in in figure TA9 and also available per `http://siteresources.worldbank.org/EXTECAREGTOPPRVSECDEV/Resources/570954-1211578683837/Bielecki_Moodys_Rating_SME_transactions.pdf`

and Loken (2014)[13]: "We have in mind an analogy with the notorious AAA-class bonds created during the mid-2000s that led to the subprime mortgage crisis. Lower-quality mortgages —that is, mortgages with high probability of default and, thus, high uncertainty—were packaged and transformed into financial instruments that were (in retrospect, falsely) characterized as low risk".

4.4 Fact 4: later vintages did worse than earlier vintages, except for subprime AAA securities

[Insert Table 6 about here]

[Insert Table 7 about here]

We calculate the average loss rate and its standard deviation per vintage and rating, see table 6 as the vintage-specific counterpart to table 4, or even per vintage-rating-mortgage-type category, see table 7 as the vintage-specific counterpart to table 5. Loss rates mostly rose for later vintages. For example, while there were nearly no losses on AAA-rated securities issued before 2003, their cumulated losses rose to nearly 5 percent for securities issues in the years 2006-2008. It probably does not come as a surprise that later vintages did worse. What may still be up to interpretation is whether this bad performance of the late-vintage RMBS occurred due to the bad luck of issuing securities based on mortgages at the peak of the housing boom, or whether some rating drift was at work. We shall return to that issue, when discussing our seventh fact. What is particularly remarkable here, however, is the stability of the loss rates for the AAA-subprime segment, as the last three columns of the top line of table 7 or the lowest line of the left panel in the middle row of figure TA6 shows: loss rates there were below 0.7% even for the subprime-AAA RMBS issued in the years 2006-2008. These tables, the figure and the remarks thus establish our ***fourth fact***: **later vintages did worse than earlier vintages, except for subprime AAA securities.** Thus, even when controlling for the vintage, it remains a fact that AAA-rated Prime and Alt-A RMBS exhibit loss rates that are worse than AAA-rated subprime-RMBS, while the performance for lower ratings is comparable. We view this as providing supportive evidence for the lower screening effort exerted by financial institutions that found easier to securitized and sell loans of higher-quality borrowers, as documented by Keys et al. (2009, 2010, 2012).

[13] We have chosen this quote because it is quite representative of the conventional narrative during the crisis and useful for our purposes. We have not chosen it as a critique of the article by Gelman and Loken (2014), whose subject of interest is not the RMBS market per se

4.5 Fact 5: the bulk of the losses were concentrated on a small share of all securities.

[Insert Figure 2 about here]

The standard deviations shown in, say, table 7 imply that not all securities behaved the same. Indeed, figure 2 shows that the loss distribution is nearly bimodal. The left panel shows the loss distribution across all RMBS, weighted by principal amount. About 65 percent of the securities lost nothing or less than 5 percent, whereas nearly 20 percent of all securities lost more than 95 percent or even everything. The right panel of figure 2 shows that distribution broken down by credit rating. One can see the same bimodality, rating-by-rating. For the AAA-rated securities, we obviously obtain a much larger share in the "near-to-no" losses bin, but even there, the worst bin contains more securities, weighted by principal amount, than those bins for losses anywhere between 40 and 80 percent. A similar statement in reverse holds for the non-investment grade bonds. With this, we establish our ***fifth fact***: **the bulk of the losses were concentrated on a small share of all securities.**

4.6 Fact 6: the misrating for AAA securities was modest

In this section, we examine the relationship of the ex-ante ratings and other bond characteristics to the ex-post performance. This may help shed light on the question of the appropriateness of the ratings. Obviously, we only see one particular history unfold, and all securities were subject to one large aggregate turn of events: one therefore needs to read this comparison with the appropriate grain of salt.

We present two exercises. In the **first exercise**, we compare the realized losses of securities to Moody's expected losses by rating. Moody's has published a table of "Idealized Cumulative Expected Loss Rate" which we present as reference in the technical appendix in figure TA9.[14] For example, in 10 years a BBB- security would be expected to have a loss rate of approximately 3.35%. For each security, we assign an "ex-post rating" based on its actual realized loss rate, converting it into the rating using the loss table by Moody's at the six-year horizon to 10-year horizon, depending on the vintage of the security. For a 2008 security we use the six-year horizon, for a 2007 a seven year horizon, and so forth. So, if a given security had a realized loss rate between the AAA and the AA expected loss rate on Moody's table (between 0.0055% and 0.22% in 10 years), the security receives an ex-post rating of AA. We then compare the

[14]The table is originally available here `https://www.moodys.com/sites/products/productattachments/marvel_user_guide1.pdf` or here`http://siteresources.worldbank.org/EXTECAREGTOPPRVSECDEV/Resources/570954-1211578683837/Bielecki_Moodys_Rating_SME_transactions.pdf`

ex-ante rating with the ex-post rating. Figure 3 presents the resulting distributions. The solid line is the fraction of securities by original rating (ex-ante), whereas the dotted line shows the distribution of the constructed ex-post rating. Overall, the share AAA ratings is the same in both distributions, though there are more securities receiving investment grade ratings ex-ante rather than ex-post.

[Insert Figure 3 about here]

[Insert Figure 4 about here]

Figure 4 shows the fraction of securities for which ex-ante and ex-post ratings coincide (labeled as Correct Rating), those for which the ex-post rating is higher than the ex-ante rating (labeled as Deflated Rating), and those for which the ex-post rating is lower than the ex-ante rating (labeled as Inflated Rating). While about 75% of AAA securities had little to no losses, thus justifying their ex-ante ratings ex post, securities with ratings A and below had a large fraction of inflated ratings. Figure TA10 in the technical appendix provides a three-dimensional version. These two figures reflect the bimodality of the loss distribution, summarized by our fifth fact.

In the **second exercise**, we wish to understand, whether the ratings could have been improved upon at the time, aside from the overall extent of the losses examined above. We seek to calculate the extent to which the inclusion of additional covariates X, available at the time of rating, for a higher-ranked security predicts larger loss probabilities than observed on average for lower-ranked securities. We call this a ratings reversal. Obviously, the information in these covariates would have been useful ex ante only to the extent that their influence on the losses ex post was understood. This is unlikely to be fully the case. One should therefore view our exercise as the best possible scenario for potentially improving on the ex-ante ratings.

More precisely, for any given $\alpha \in [0, 1]$, which we shall call the loss threshold, as well as for each rating, say AAA, we first seek to estimate $P(Loss > \alpha \mid AAA)$ and $P(Loss > \alpha \mid AAA, X)$, given the crisis of 2008. For the former, we estimate this probability with the fraction of AAA-securities, whose losses exceeded α at the end of 2013. For the latter and for each security i rated AAA and with covariates X_i, construct the observation

$$Y_i = 1_{Loss_i > \alpha}$$

indicating, whether the losses for security i exceeded α or not. As covariates, we made use of the available covariates in our data that we deemed possible predictors of the losses, so as to capture what the rating actually adds or misses. Examples include the information we have on

FICO scores and LTV ratios. The available covariates were briefly listed in subsection 3.1 and described in detail in section 2 of the on-line database appendix[15]. We then estimate a linear probability model, per linear regressing these observations Y_i on the covariates X_i. Different values for α generally result in different estimates.

For the ratings AAA and AA, say, we define the gain from including covariates X compared to the raw probability difference as

$$Gain_{AAA,AA}(\alpha) = \frac{E\left[\left|P(Loss > \alpha | AAA, X) - P(Loss > \alpha \mid AAA)\right|\right]}{P(Loss > \alpha \mid AAA) - P(Loss > \alpha \mid AA)} \tag{1}$$

where the outer expectation is taking an expectation over the random covariates X. We estimate the numerator by the sample average of $\hat{P}(Loss > \alpha | AAA, X_i) - \hat{P}(Loss > \alpha \mid AAA)$ for all AAA-rated securities i and the probability estimators explained above. We likewise define $Gain_{AAA,A}(\alpha)$, $Gain_{AA,A}(\alpha)$, etc.. We define the probability of rating reversals for AAA-rated securities to AA securities as

$$Reversal_{AAA,AA}(\alpha) = P\left(P(Loss > \alpha \mid AAA, X) > P(Loss > \alpha \mid AA)\right)$$

where the outer probability is likewise taken as an expectation over the random covariates X. We estimate $Reversal(\alpha)$ by calculating the fraction of all AAA-rated securities i, for which $\hat{P}(Loss > \alpha \mid AAA, X_i)$ exceeds $\hat{P}(Loss > \alpha \mid AA)$, with $\hat{P}(\cdot)$ denoting the estimator of $P(\cdot)$ explained above. We likewise construct estimators for $Reversal_{AAA,A}(\alpha)$, $Reversal_{AA,A}(\alpha)$, etc.. We explore different values for α to fully understand the landscape of these gains and rating reversals.

[Insert Table 8 about here]

[Insert Table TA5 about here]

Panel A of Table 8 reports estimates of the gains given by equation 1, for all the pairwise comparisons between a given rating and ratings below it for investment grade RMBS. We see that covariates did carry information that would have been useful to predict losses, and to assign ratings, particularly for the AA, A, and BBB ratings. For AAA ratings, we some gains from the covariates only for low values of alpha. The estimates of rating reversals is reported in panel B of Table 8. It turns out that the value of α matters considerably. If $\alpha = 0$, then we find a 40 percent probability of rating reversal. To understand this, consider the probability of the occurrence of any loss, as shown in table TA5. It turns out that AAA securities were actually

[15]For a detailed list of the covariates employed, refer to MBS Project/Replication/DefaultsAnalysis/Step7

somewhat more likely to incur losses than AA securities: the overall fractions are 28 percent versus 16 percent. We know already, however, that losses on AAA securities are typically small, if they occur at all. Figure 2 shows that the distribution for AAA securities puts more weight on small losses compared to the distribution for other investment grade securities. Thus, as α is increased to, say, 10%, we find a rating reversal probability of only 3%.

A loss threshold of $\alpha = 0$ is perhaps very stringent to judge the appropriateness of the rankings, especially in light of the crisis. Perhaps a loss threshold of $\alpha = 0.1$ or 10%, for which rating reversals are now rare, is quite large, in particular for highly rated securities, though perhaps not dramatically large, given the unfolding of the crisis and given our purposes here. Overall we judge that the rating agencies got the rankings about right, in particular for the AAA-rated securities. We therefore summarize the findings from both exercises as our ***sixth fact***: **the misrating for AAA securities was modest.**

This interpretation and these numbers come with a number of caveats, of course. First, the construction of the securities often implies mechanically, that lower-ranked securities will be hit with losses before that happens to higher-ranked securities. The ranking of securities for any given deal is therefore very unlikely to be incorrect (assuming that rating agencies did indeed check the loss sequencing): the comparison here is more interesting regarding the consistency of rankings for securities across deals. Second, all our inference is conditional on the crisis of 2008: this is the only set of observations we got. We obviously cannot infer anything here about the appropriateness of the ratings or their rankings across all potential futures from 2007 on forward. Finally, we have used the realized losses to estimate the weight on information available a priori, in order to check for rating reversals. Obviously, the rating agencies did not have that information at hand at the time when they had to give their assessments.

4.7 Fact 7: a home price boom was good for repayments.

Given our fourth fact, can we therefore conclude that ratings deteriorated over time and that rating agencies became more generous? This certainly has been a theme in much of the conventional narrative of the crisis. Given the evidence compiled for our forth fact, we cautiously share the view that rating standards have indeed deteriorated in the run-up to the crisis. Moreover, these results are consistent with the findings of Adelino et al. (2015), who argue that middle income borrowers had an increasing relative role in mortgage delinquencies and defaults in the run-up to the crisis. These results are also consistent with the idea that securitization contributed to bad lending by reducing incentives of lenders to carefully screen borrowers, and that lower screening standards happened for relatively high FICO scores as those loans were easier to securitize as argued by Keys et al. (2010).

The deterioration in performance could also have been due to bad luck, though. Consider a security issued long before the peak of the house price boom, and compare it to an otherwise identical security issued just at the peak. The former security is less likely to be subject to losses, since the 2013 value of the underlying home relative to the original purchase price is higher for the former compared to the latter. If one views the arrival of the house price decline as a random event, unrelated to current level of house prices, one could argue that the resulting higher losses for the later vintages were just a stroke of bad luck, and not the result of a more liberal rating.

[Insert Table 9 about here]

To explore this issue, we exploit the cross-state variation in house price developments as well as the state-specific performance of the RMBS. For each security in our data set, we know the top five states in terms of the locations of the underlying mortgages, and the fraction of the total principal invested there. In table 9, we estimate a linear regression of the cumulative loss as a fraction of initial principal on the change in house prices, both during the run-up phase from 2000-2006 as well as the crash-phase from 2006-2009. To find the house price change relevant for each RMBS, we have averaged the house price changes over the five top states in which that security was invested, using the relative investment shares to calculate these averages. Our preferred specifications are in columns (3) and (4). There, we find that the increase in house prices decreased losses, but that the subsequent decrease in house prices increased losses for the security. According to column (4), say, an additional increase of house prices from 2000 to 2006 decreased losses by 0.18 percent of principal, while an additional decline of house prices from 2006 to 2009 by one percent increased losses by 0.53 percent. Column (3) provides a rather similar answer. If only the price increase is included or if state dummies are included, with the weights given by the investment shares, these effects (rather naturally) disappear. We summarize the key insight with our ***seventh fact***: **controlling for a home price bust, a home price boom was good for the repayment on these securities.** The results show that it is really the bust, not the boom, which adversely affected the repayments. As an implication, securities issued at a later date were exposed to more of the bust and less to the boom, making their losses more likely. Fact 4 holds up even after controlling for the house price boom and bust. The results of the technical appendix shown in figures TA5 through TA8 control for house prices. It does seem, that the credit rating agencies did lower their standards, notwithstanding the fact shown here that exposure to house prices did affect repayments and may have been (at least partially) missed in the rating process.

5 Returns

AAA securities in particular play a special role, in that they are considered to be safe investments. It should be clear from the facts presented so far, that they were not safe, as a group, and that some indeed defaulted dramatically. A complementary perspective is to ask, how much money investors gained or lost from holding these securities to maturity, i.e. to calculate their rates of returns. This is the purpose of this section. Only investment-grade securities were sold at par: so we focus on these.

We have calculated these returns in two ways. The first is to calculate the internal rate of return. This is the rate r that solves net present value equation

$$P_0 = \sum_{t=1}^{T} \frac{i_t + p_t}{(1+r)^t} + \frac{TV_T}{(1+r)^T} \tag{2}$$

where P_0 is the initial value of the security and equal to the principal amount, i_t is the monthly cash flow corresponding to interest payments, p_t is the monthly cash flow corresponding to principal paydown, and TV_T is the terminal value at some date T. The second is to calculate the implied premium θ over a benchmark interest rate r_t, solving

$$P_0 = \sum_{t=1}^{T} \frac{i_t + p_t}{\left(1 + r_t^{t\_bill} + \theta\right)^t} + \frac{TV_T}{\left(1 + r_t^{t\_bill} + \theta\right)^T} \tag{3}$$

This perspective may be particularly appropriate for floating-interest rate mortgages. For the benchmark r_t, we are using the 3-month Treasury Bill. Note that we do not take into account risk prices or term premia in either calculation.

We set T to be December 2013, given our data set. We observe the original principal amount P_0, payments i_t as well as p_t, but we do need to make assumptions regarding the terminal value TV_T. The natural candidate for the terminal value is the outstanding principal balance at time T, which is part of the monthly information that we have for each security. To that end, it is important to understand how past losses affect the outstanding principal value in the data. In a typical prospectus for an RMBS one can find the explanation: realized losses are applied to reduce the principal amount and "if a loss has been allocated to reduce the principal amount of your class of certificates, you will receive no payment in respect of that reduction." From this we conclude that the principal balance recorded in the data at date T already incorporates losses on principal that have occured previously rather than leaving them on the book. However it is possible that there needs to be some additional discounting of the outstanding principal value, because additional losses may be expected in the future. We therefore examine three different scenarios regarding the terminal value, and assume that all securities are valued at 80%, 90% and 100% of the principal outstanding as of December 2013. In the technical appendix, we provide results for an additional three scenarios, to examine robustness. For the fourth scenario, we assume that each security trades at a loss equal to the loss rate it has suffered up to that point. For the fifth, we assume that each security trades at a loss equal to the mean loss rate of the securities with the same original credit rating and same vintage. The sixth is similar to the fifth, except for using the median loss rate rather than the mean. The overall results did not seem to change much.

[Insert Figure 5 about here]

[Insert Table 10 about here]

[Insert Table 11 about here]

To provide a perspective for the (first) three scenarios shown here, we consulted information provided by FINRA for the month of December 2013, see figure 5. In 2009, the Financial Industry Regulatory Authority (FINRA) made a proposal to collect data for ABS, CDO, and MBS securities.[16] Now daily reports going back to May 2011 with the number of transactions, trade volume, and statistics on transaction prices are publicly available.[17]. From these reports one can see that, as of December 2013, investment-grade securities were mostly trading with prices above 90, and non-investment grade with prices above 75 and generally above 80. We therefore consider our range from 80 to 100 percent to be reasonable.

Table 10 presents results for the realized internal rate of return calculations, for the first three scenarios regarding the terminal value. These results are echoed by the corresponding premium calculations in table 11. It may therefore suffice to comment on the first of these two tables. The most important result here may be that AAA securities provided an internal rate of return of about 2.44% to 3.31%, depending on the scenario. It mattered quite a bit, whether the mortgages were fixed rate or floating rate. For fixed rate mortgages, AAA securities returned between 3.6 and 4.8 percent, depending on the market segment and assumptions regarding the terminal value. For floating rate mortgages, AAA securities returned between 0.4 and 3.8 percent. These results show about a 2 percentage point realized premium of Prime over Subprime securities. This may be surprising at first given that we showed that losses in subprime securities were not particularly worse than in other segments and for AAA were actually lower. One reason behind this is the fact that the fraction of floating rate bonds (almost 90%) in

[16] https://www.finra.org/newsroom/2009/finra-proposes-expanding-trace-reporting-asset-backed-securities

[17] Reports are available and can be downloaded at http://tps.finra.org/idc-index.html

the subprime segment was higher than the fraction of floating rate bonds in the Alt-A (about 62%) and Prime (about 46%) segments. In a period of low interest rates like the one we consider, floating rate bonds did worse than fixed rate bonds. Overall, though, these returns and premia on AAA RMBS strike us as rather reasonable. It surely is an interesting challenge to construct a theory around these realized returns, which despite being positive above the risk free benchmark, the conventional narrative puts them at the heart of what resulted in a disaster for the world-wide financial system. Finally, tables TA7, TA8, TA9, TA10 in the technical appendix show calculations of the return premium based on individual securities as opposed to pooling cash flows together.

6 Discussion and Conclusion

We have examined the payoff performance, up to the end of 2013, of non-agency residential mortgage-backed securities (RMBS), issued up to 2008. For our analysis, we have created a new and detailed data set on the universe of non-agency residential mortgage backed securities, per carefully assembling source data from Bloomberg and other sources. We have compared these payoffs to their ex-ante ratings as well as other characteristics. We have established seven facts. Together, these facts call into question the conventional narrative, that improper ratings of RMBS were a major factor in the financial crisis of 2008 as well as create an intriguing quantitative challenge to theorists seeking to explain the meltdown of the world-wide financial system due to the performance of highly rated RMBS.

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7 Figures and Tables

Table 1: **RMBS Database: Deals, Securities, Nominal Amounts by Year of Issuance**

This table reports some figures that describe the size of our database of Residential Mortgage Backed Securities by year of issuance. All the information comes from Bloomberg. The securities included in our final database were issued between 1987 and 2013.

Year	No. Deal Managers	No. Deals	No. MBS	Notional ($ Billion)	Average Deal Size ($ Million)
1987 - 1999	35	858	9,462	244.2	284.6
2000	20	227	2,724	93.8	413.2
2001	23	397	5,815	179.9	453.1
2002	30	574	8,255	314.0	547.1
2003	30	788	12,420	475.1	603.0
2004	30	1,106	15,787	723.4	654.1
2005	29	1,361	22,017	1,005.2	738.5
2006	39	1,563	27,184	1,237.4	791.7
2007	35	1,027	19,143	936.1	911.5
2008	20	108	1,541	103.3	956.4
2009	17	151	5,660	170.6	1,129.9
2010	17	135	6,089	155.9	1,154.5
2011	13	101	3,182	68.3	676.5
2012	11	92	1,789	36.5	396.9
2013	13	127	2,164	98.7	776.9
All Years	83	8,615	143,232	5,842.3	678.2

Table 2: **Database Variables**

This table lists some of the data and variables that we gathered from Bloomberg and the 2013 Mortgage Market Statistical Annual about each of the non-agency Residential Nortgage backed Securities in our data. Section 2 in the on-line data appendix contains a detailed description of the variables in our dataset.

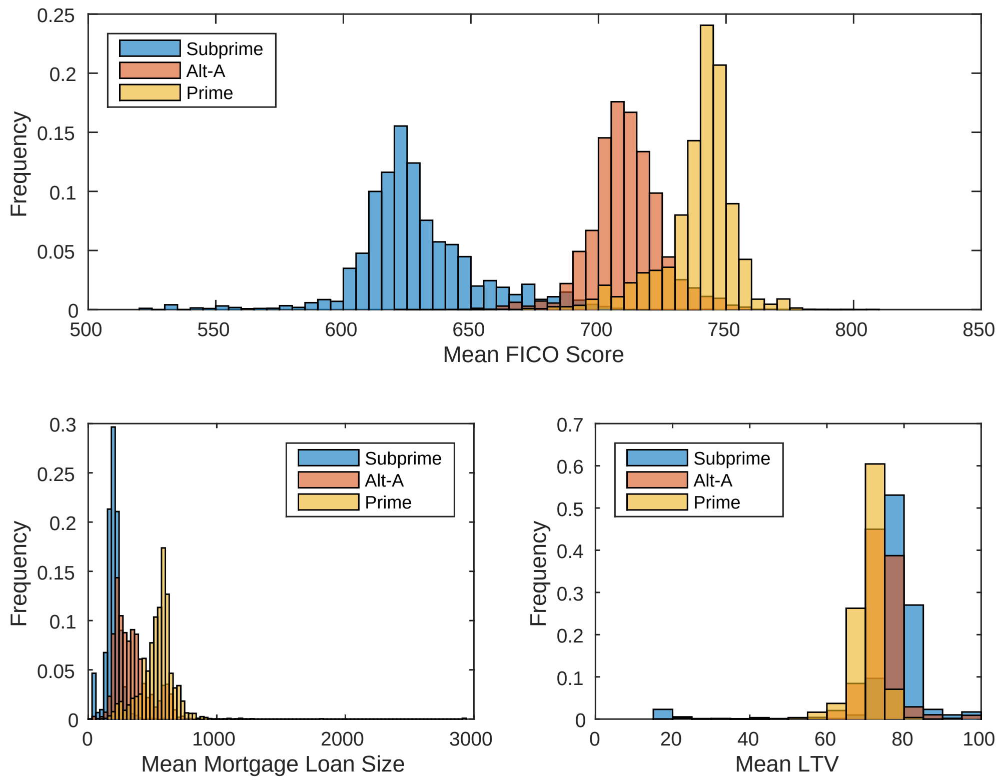
Security Identification	***Credit Rating***
Cusip ID	Current and Original Ratings (5 agencies)
Deal Name	***Other Security Characteristics***
Deal Manager	Credit Support at Issuance
Issuer Company	Original Principal Amount
Security Classification	***Collateral Description***
Deal Type (eg. CMBS, RMBS)	Mortgage Purpose (% Equity Takeout, Refinance)
Collateral Type (eg. Home, Auto, Student)	LTV Distribitution (min, max, mean, 25th, 50th,75th)
Collateral Type (eg. ARM vs FRM)	Credit Score Distribution (min, max, mean, 25th, 50th,75th)
Agency Backed (yes, no)	Mortgage Size Distribution (min, max, mean, 25th, 50th,75th)
Agency (eg. Fannie Mae, Freddie Mac)	MBS metrics 1: Weighted Average Coupon
Dates	MBS metrics 2: Weighted Average Life
Issue Date	MBS metrics 3: Weighted Average Maturity
Pricing Date	Fraction of adjustable-rate (ARM) and fixed-rate (FRM) mortgages
Maturity Date	Occupancy (% of Owner, Investment, Vacation)
Security Description	***Geographic Information***
Bond type (e.g. Floater, Pass-through, Interrest Only)	Fraction of mortgages in top 5 states
Tranche Subordination Description	***Cash Flow and Losses***
Coupon Type (e.g. Fixed, Floating)	Monthly Interest and Prinicipal Payment
Coupon Frequency (e.g. Monthly)	Monthly Outstanding balance
Coupon Index Rate (e.g. 3M-libor)	Monthly Losses

Table 3: **Non-Agency RMBS 1987-2013: Credit Rating Composition**

This table shows the total of principal amounts by credit rating. The credit rating corresponds to the rating assigned to a bond upon issuance. If several ratings were given, we have taken an average. This table illustrates fact 1: The great majority of non-agency RMBS securities were assigned a AAA rating upon issuance. The calculations in this table include all securities in the database, even those issued after 2008.

Rating	$ Billion	Pct.
AAA	4,535.1	86.9
AA	297.0	5.7
A	212.3	4.1
BBB	118.4	2.3
BB	40.1	0.8
B	13.6	0.3
CCC	0.3	0.0
CC	0.6	0.0
C	3.3	0.1
Rated	5,220.5	91.7
Not Rated	472.1	8.3

Figure 1: **Distribution of Mean FICO Score, Loan Size, and LTV by Type of Loan**



This figure plots the distribution of the mean FICO score, the mean mortgage loan size and the mean loan to value ratio (LTV) for Residential Mortgage Backed Securities issued between 2006 and 2012 and classified by type of mortgage backing the securities. The classification is done based on information in the Statistical Annual while the data on scores, loan size and LTV is from Bloomberg.

Table 4: **RMBS Losses as of December 2013, by credit rating.**

This table shows the principal amount at issuance as well as the cumulated losses, as of December 2013, broken down by credit rating. We exclude all the MBS bonds for which the original principal amount is only a reference or that can distort our computations. The excluded bonds include bonds with zero original balance, excess tranches, interest-only bonds, and Net Interest Margin deals (NIM). Only bonds issued up to 2008 are part of the computations.

	Principal Amount	Losses	Percentage
All RMBS	4,965.6	313.7	6.3
AAA	4,402.4	94.9	2.2
AA	263.7	87.4	33.1
A	144.9	56.3	38.8
BBB	101.6	47.7	46.9
NIG	53.1	27.9	52.6

Table 5: **RMBS Losses as of December 2013, by credit rating and mortgage type.**

This table shows the principal amount at issuance as well as the cumulated losses, as of 2013, broken down by credit rating and mortgage type (Prime, Alt-A, and Subprime).

	Principal Amount	Losses	Percentage
All Securities			
Prime	1,238.7	37.5	3.0
Alt-A	1,327.3	145.2	10.9
Subprime	1,196.0	119.1	10.0
AAA Rated Securities			
Prime	1,172.7	14.8	1.3
Alt-A	1,210.0	78.9	6.5
Subprime	979.5	4.3	0.4
Investment Grade Ex-AAA Securities			
Prime	54.0	18.4	34.0
Alt-A	96.5	55.3	57.3
Subprime	203.9	104.8	51.4
Non-Investment Grade Securities			
Prime	12.0	4.3	36.2
Alt-A	20.8	10.9	52.7
Subprime	12.7	10.0	78.7

Table 6: **Principal-Weighted Losses in RMBS and Credit Ratings**

This table shows regressions of the cumulative loss as fraction of initial principal as of December 2013 on credit rating dummy variables. The regressions are weighted by the principal dollar amount upon issuance of each RMBS. The constant of the regression corresponds to AAA securities, and we have renamed the constant as AAA. The first column shows the results for the entire sample, i.e. all securities issued since 1987 through 2008. The next 3 columns split the sample by year of issuance into three periods.

Credit Rating	**Full Sample**	**Before 2003**	**2003 - 2005**	**2006-2008**
AAA	0.0218***	0.0002	0.0034***	0.0483***
	(0.0006)	(0.0001)	(0.0007)	(0.0011)
AA	0.3096***	0.001	0.1180***	0.5091***
	(0.0025)	(0.0008)	(0.0028)	(0.0043)
A	0.3620***	0.0055***	0.2000***	0.6572***
	(0.0033)	(0.0008)	(0.0036)	(0.0062)
BBB	0.4480***	0.0334***	0.3152***	0.6655***
	(0.0040)	(0.0013)	(0.0041)	(0.0072)
BB	0.4923***	0.0653***	0.4886***	0.5136***
	(0.0064)	(0.0029)	(0.0075)	(0.0102)
B	0.5812***	0.0938***	0.6989***	0.5619***
	(0.0117)	(0.0042)	(0.0147)	(0.0182)
CCC	0.7360***	0.4125***	0.4102***	0.9465***
	(0.0867)	(0.0558)	(0.0987)	(0.1361)
CC	0.2036***	0.1364	0.0251	0.2005***
	(0.0562)	(0.0964)	(0.1228)	(0.0719)
C or Below	0.3863***	0.0661***	0.6607***	0.3604***
	(0.0225)	(0.0227)	(0.1665)	(0.0274)
Observations	93,902	19,230	38,381	36,291
R-squared	0.3217	0.0852	0.2972	0.485

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: **Losses and Credit Ratings by Vintage Group and Type of Mortgage Loan**

This table presents principal-weighted regressions of the cumulative loss as fraction of initial principal as of December 2013 on credit rating dummy variables for all the RMBS in our database issued through 2008 classified by the type of mortgage loan underlying the securities and by 3 vintage groups.

	Prime			**Alt-A**			**Subprime**		
Rating	**Before 2003**	**2003 - 2005**	**2006 - 2008**	**Before 2003**	**2003 - 2005**	**2006 - 2008**	**Before 2003**	**2003 - 2005**	**2006 - 2008**
AAA	0.0000	0.0032***	0.0259***	0.0002	0.0076***	0.0953***	0.0004	0.0013	0.0068***
	(0.0001)	(0.0008)	(0.0015)	(0.0003)	(0.0015)	(0.0015)	(0.0008)	(0.0018)	(0.0020)
AA	0.0001	0.2242***	0.5841***	0.0045**	0.2097***	0.7824***	0.0007	0.0348***	0.6260***
	(0.0007)	(0.0052)	(0.0093)	(0.0019)	(0.0060)	(0.0080)	(0.0040)	(0.0061)	(0.0061)
A	0.0006	0.2837***	0.3071***	0.0080***	0.3620***	0.7260***	0.0151***	0.1566***	0.7600***
	(0.0011)	(0.0075)	(0.0117)	(0.0027)	(0.0094)	(0.0119)	(0.0050)	(0.0077)	(0.0078)
BBB	0.0039***	0.3065***	0.2957***	0.0267***	0.4728***	0.5161***	0.0718***	0.3609***	0.8654***
	(0.0013)	(0.0088)	(0.0146)	(0.0033)	(0.0115)	(0.0117)	(0.0058)	(0.0091)	(0.0094)
BB	0.0163***	0.2850***	0.2303***	0.0499***	0.6415***	0.3546***	0.1113***	0.5755***	0.8861***
	(0.0021)	(0.0095)	(0.0143)	(0.0054)	(0.0173)	(0.0144)	(0.0199)	(0.0191)	(0.0166)
B	0.0336***	0.7159***	0.8828***	0.0863***	0.7765***	0.4816***	0.2448***	0.5133***	0.7463***
	(0.0026)	(0.0165)	(0.0344)	(0.0075)	(0.0254)	(0.0193)	(0.0419)	(0.0580)	(0.0495)
CCC	-	0.2474**	0.9484***	0.9710***	0.6840***	0.8850**	-	0.3836**	0.9931***
	(0.0754)	(0.1091)	(0.2731)	(0.0866)	(0.1954)	(0.3523)	(0.0977)	(0.1949)	(0.1512)
CC	-	0.0109	-	-	-	0.6322***	-	0.1189	-
	(0.1109)	(0.0951)	(0.2628)	(0.1027)	(0.0977)	(0.1078)	(0.1027)	(0.3823)	(0.5566)
C or Below	-	0.7679***	0.9687	0.4963***	-	0.3112***	-	0.3775	0.9932**
	(0.1215)	(0.1359)	(0.5928)	(0.0449)	(0.0219)	(0.0241)	(0.1369)	(0.3712)	(0.5020)
Observations	4,095	13,366	8,015	2,908	8,226	16,001	1,363	6,028	11,314
R-squared	0.0554	0.3468	0.4182	0.1571	0.4329	0.4975	0.1432	0.3217	0.7052
Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: **Credit Rating Reversals**

Panel A presents the calculation of equation (1). Panel B presents the incidence of credit rating reversals. Using our estimated probability model that uses the covariates in our database we compute the fraction of securities of a given credit rating for which we would have predicted a probability of loss bigger than the probability of loss of a lower credit rating if we had had all the information upon issuance. For example, for AAA that switched to AA we compute the fraction of RMBS such that $P(Loss > \alpha | AAA, X) > G(\alpha) = P(Loss > \alpha | AA)$*).*

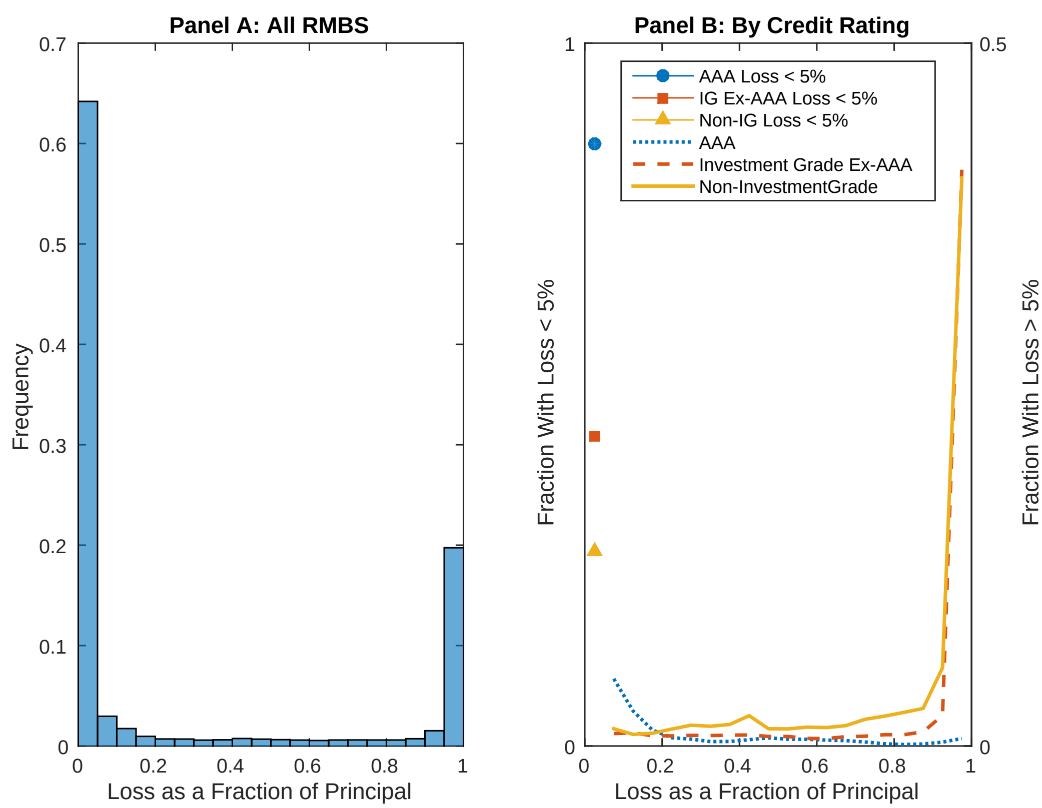
Panel A: Gains from Including Other Covariates

	$\alpha = 0$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.25$	$\alpha = 0.5$	$\alpha = 0.75$	$\alpha = 0.9$
Principal Value Weighted							
AAA vs AA	1.65	0.47	0.24	0.12	0.08	0.04	0.03
AAA vs A	2.26	0.58	0.28	0.14	0.08	0.04	0.03
AAA vs BBB	0.82	0.32	0.17	0.09	0.06	0.03	0.02
AA vs A	-8.52	-6.76	-6.69	-11.29	-20.50	-59.50	- -699.95
AA vs BBB	2.27	2.54	2.77	2.59	2.79	2.62	2.54
A vs BBB	1.90	1.94	2.07	2.32	2.82	3.02	3.11

Panel B: Credit Rating Reversals

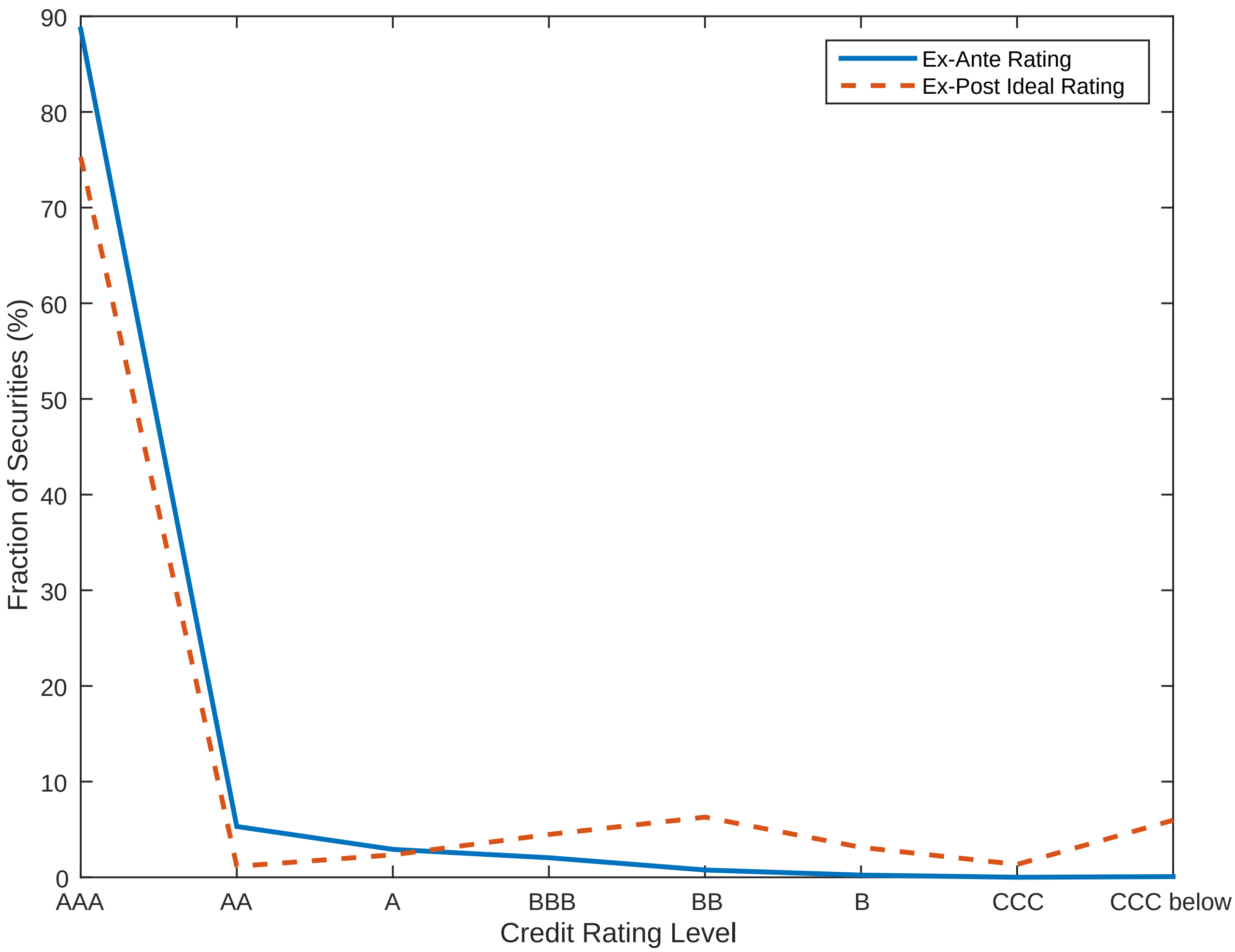
	$\alpha = 0$	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.25$	$\alpha = 0.5$	$\alpha = 0.75$	$\alpha = 0.9$
Principal Value Weighted							
AAA switched to AA	49.9	13.9	1.0	0.3	0.3	0.0	0.0
AAA switched to A	54.5	21.4	2.3	0.3	0.3	0.0	0.0
AAA switched to BBB	31.2	2.8	0.4	0.3	0.2	0.0	0.0
AA switched to A	75.4	73.2	72.8	71.7	69.0	67.4	66.1
AA switched to BBB	63.8	63.1	63.1	62.8	60.9	59.2	57.8
A switched to BBB	67.4	67.7	67.9	68.1	68.5	67.3	65.4

Figure 2: **Distribution of Loss Size for All RMBS**



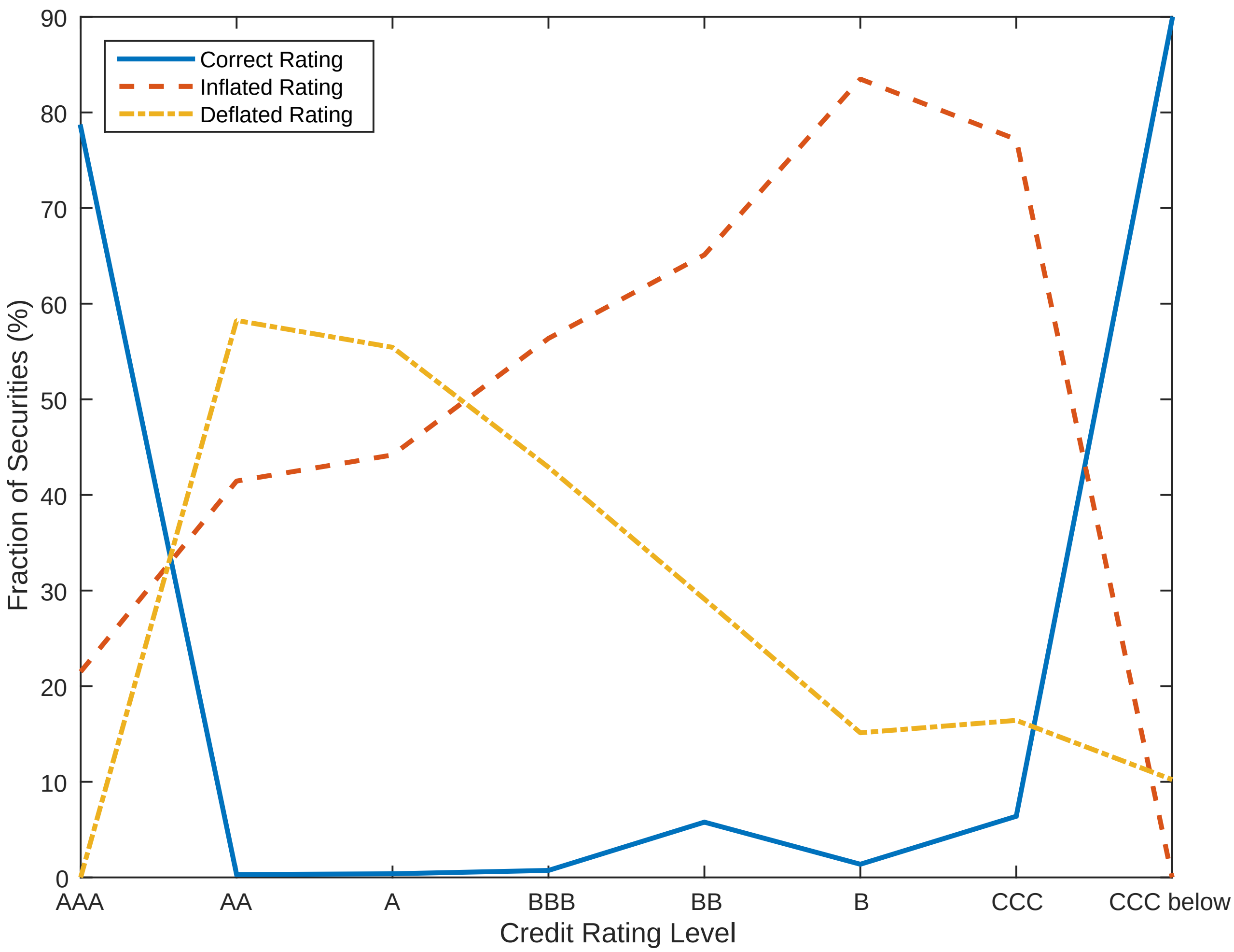
Panel A presents the distribution of cumulative losses as of December 2013 as a fraction of the original principal amount for all the RMBS in our database issued from 1987 through 2008. Panel B shows the distribution of cumulative losses as of December 2013 as a fraction of the original principal amount for different groups of RMBS based on the type of the underlying mortgage loans.

Figure 3: **Ex-Ante vs Ex-Post Ideal Ratings**



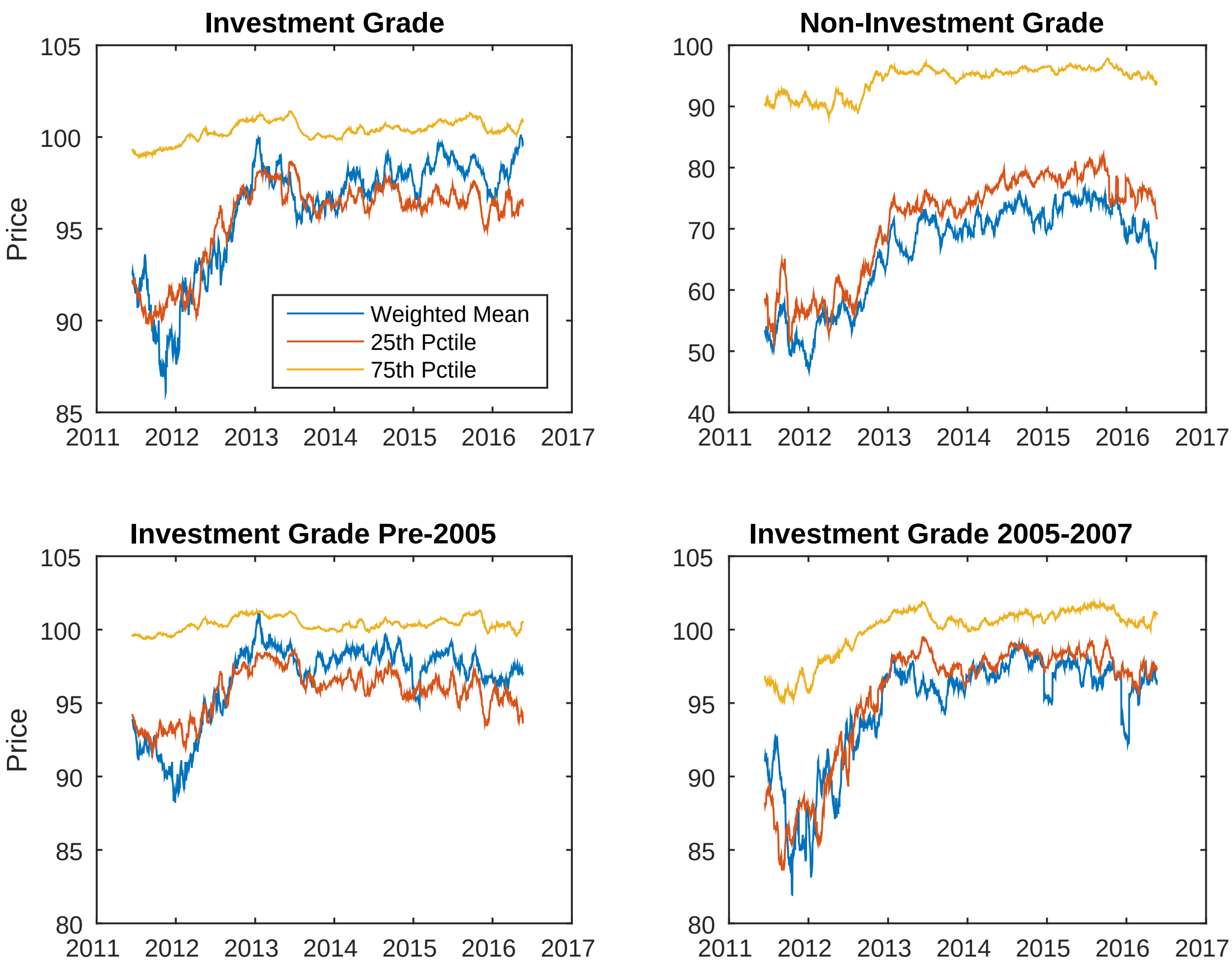
In this figure, for each security, we compare the original credit rating (which we call here Ex-Ante Rating) to the rating that ex-post we would have assigned given the security's realized loss using Moody's idealized Expected Loss Table by Rating, which we present in Figure TA9 in the technical appendix. The solid line shows the fraction of securities that was assigned each rating level. The dotted line shows the fraction of securities that should have gotten each rating level based on their loss as a fraction of original principal. The calculations are all weighted by dollar value of principal

Figure 4: **"Right" and "Wrong" Ratings Based on Moody's Ideal Ratings**



This figure compares the original rating of each security to the rating we would have assigned ex-post based on Moody's idealized Expected Loss Table by Rating. If the two ratings coincide, we say that the security was correctly rated. If the original rating is higher than what it should have been based on realized losses, we say that the security had an inflated rating. Finally, if the original rating is lower than what it should have been based on realized losses, we say that the security had a deflated rating. The calculations are all weighted by dollar value of principal.

Figure 5: **Summary Statistics of Prices Collected by FINRA**



This figure shows summary statistics of daily transaction prices collected by the Financial Industry Regulatory Authority from May 2011 through May 2016 on Non-Agency MBS. The plots at the top break up the statistics by Investment Grade and Non-Investment Grade, while the plots at the bottom break up the statistics by groups of vintages only for Investment Grade securities. FINRA produces this information daily since 2011. The lines in the different figures correspond to 22-day moving averages (daily monthly averages) of the daily values reported by FINRA. Here we report the principal weighted average and the 25th and 75th percentiles of the average transaction price. The daily reports are available here `http://tps.finra.org/idc-index.html`

Table 9: **House Prices and Loss Rates**

This table presents linear regressions to study the relation between the the cumulative loss as fraction of initial principal as of December 2013 and changes in house prices. The variables on the RHS include the variables ΔHP 2000-2006 and ΔHP 2006-2009 which is the appreciation of house prices between 2000 and 2006 and between 2006 and 2009 in the five states that for each MBS have the highest share of the underlying mortgages.

	(1)	(2)	(3)	(4)	(5)
ΔHP 2000 - 2006	0.073***		-0.218***	-0.178***	-0.021
	0.003		0.010	0.012	0.027
ΔHP 2006 - 2009		-0.203***	-0.63***	-0.532***	0.342***
		0.006	0.021	0.020	0.061
AA				0.426***	0.423***
				0.003	0.003
A				0.493***	0.488***
				0.004	0.004
BBB				0.555***	0.55***
				0.005	0.005
BB				0.5***	0.492***
				0.007	0.007
B				0.599***	0.594***
				0.013	0.012
CCC				0.749***	0.74***
				0.087	0.086
CC				0.496***	0.493***
				0.089	0.087
C or Below				0.324***	0.305***
				0.023	0.022
Subprime				0.009***	-0.003*
				0.002	0.002
Alt-A				0.049***	0.032***
				0.002	0.002
Contstant	0.011***	-0.001	0.019***	-0.038***	0.059***
	0.002	0.002	0.002	0.005	0.007
State Dummies	No	No	No	No	Yes
Weighted Dummies	No	No	No	No	Yes
Observations	93,902	93,902	93,902	71,316	71,316
R-squared	0.0059	0.0107	0.0156	0.4345	0.4513
Weighted	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 10: **Internal Rate of Return Calculations From Issuance to 2013 by Credit Rating and for AAA also by Type of Mortgage.**

This table presents Internal Rate of Return (IRR) calculations for the RMBS in our database by type of mortgage loan. The IRR solves equation 2. Here we report annualized rates. We present the computation under different assumptions about the terminal value of each security as of December 2013. The 3 columns assume that the security is sold at 80%, 90% and 100% of the outstanding principal amount as of December 2013 respectively. The calculation was done by pooling together the cash flowsof all bonds and creating a super bond.

Return Statistic	**80% TV**	**90% TV**	**100% TV**
By Credit Rating			
AAA	2.44	2.89	3.31
AA	-7.90	-7.01	-6.21
A	-10.92	-10.10	-9.35
BBB	-13.56	-12.80	-12.11
Inv. Grade Ex AAA	-9.01	-8.15	-7.38
By Type of Mortgage			
AAA Prime	3.61	3.98	4.33
AAA SubPrime	1.61	2.14	2.62
AAA AltA	1.37	2.01	2.61
Fixed Rate MBS			
AAA Prime Fixed	4.25	4.56	4.84
AAA SubPrime Fixed	4.86	4.96	5.04
AAA AltA Fixed	3.64	4.13	4.58
Floating Rate MBS			
AAA Prime Floating	3.03	3.45	3.83
AAA SubPrime Floating	1.45	1.97	2.44
AAA AltA Floating	0.42	1.12	1.76

Table 11: **Premium θ From Issuance to 2013 by Credit Rating AAA also by Type of Mortgage.**

This table presents premium calculations for the RMBS in our database by credit rating using the 3-month Tbill rate as benchmark. The premium IRR solves equation 3. We present the computation under different assumptions about the terminal value of each security as of December 2013. The 3 columns assume that the security is sold at 80%, 90% and 100% of the outstanding principal amount as of December 2013 respectively. The calculation was done by pooling together the cash flows of all bonds and creating a super bond.

Return Statistic	**80% TV**	**90% TV**	**100% TV**
By Credit Rating			
AAA	0.84	1.39	1.86
AA	-9.45	-8.61	-7.66
A	-12.37	-11.6	-10.9
BBB	-15.16	-14.3	-13.56
Inv. Grade Ex AAA	-10.56	-9.75	-8.83
By Type of Mortgage			
AAA Prime	2.16	2.48	2.78
AAA SubPrime	0.06	0.54	1.17
AAA AltA	-0.23	0.51	1.16
Fixed Rate MBS			
AAA Prime Fixed	2.7	2.96	3.39
AAA SubPrime Fixed	3.41	3.46	3.49
AAA AltA Fixed	2.04	2.63	3.13
Floating Rate MBS			
AAA Prime Floating	3.01	3.42	3.84
AAA SubPrime Floating	1.46	1.92	2.39
AAA AltA Floating	0.4	1.09	1.77