MBS ratings and the mortgage credit boom

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Abstract

This paper studies credit ratings on subprime and Alt-A mortgage-backed securities (MBS) deals issued between 2001 and 2007, the period leading up to the subprime crisis. We first estimate a simple summary statistic for credit risk in each deal using a loan-level econometric model based on ex-ante data. Ratings conditional on this measure of credit risk and other controls exhibit significant time-series variation, becoming more conservative initially, then less conservative between 2005 to 2007, the peak of the mortgage credit boom. Our measure of default risk is significantly correlated with ex-post deal performance, even conditional on ratings. It is also a stronger predictor of ex-post performance than credit ratings in a simple "horse race". Our evidence suggests that MBS ratings, while informative, were insufficiently sensitive to observable measures of risk, and did not respond to rising risk in the last part of the sample. We remain agnostic on whether shortcomings in ratings reflect innocent errors or incentive problems associated with the "issuer pays" credit rating model.

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1. Introduction

Many commentators have argued that mistakes by credit rating agencies (CRAs) contributed to the current financial crisis, which began with a large increase in subprime mortgage defaults in 2007 and 2008. For example, critics note that many mortgage-backed securities (MBS) originally assigned investment-grade credit ratings currently trade significantly below par, and have also been subject to significant downward rating revisions. As some supporting evidence, Figure 1 plots net rating downgrades on subprime and Alt-A MBS issued since 2001. For bonds issued in the first part of the sample, net rating changes are close to zero, implying upward rating revisions were nearly as common as downgrades. However, bonds issued at the peak of the boom have subsequently faced large downward revisions, by an average of eight to ten rating notches.

[INSERT FIGURE 1 HERE]

One interpretation of these facts, advanced by CRAs themselves, is that rating errors observed *ex-post* reflect an extremely poor realization of fundamentals, namely an unprecedented decline in house prices, as well as a sharp contraction in credit supply that prevented refinancing of subprime loans. The opposing view is that the rating process itself was flawed, either due to incentive problems or innocent mistakes in methodology, and thus that ratings were inappropriate *ex-ante*, not just *ex-post*.

The goal of this paper is to present empirical evidence to distinguish between these two views. Our analysis is based on a sample of 3,001 deals issued between 2001 and 2007, the period leading up to the crisis. Our data combines security-level information from Bloomberg and ABSNet on the structure of these deals with loan level data from LoanPerformance on the characteristics and ex-post payment performance of each individual mortgage underlying these deals, around 11 million loans in total.

Our evidence suggests that initial MBS credit ratings, although informative, are insufficiently sensitive to observable measures of credit risk during our sample period. First, for each deal vintage, we recursively estimate a simple loan-level econometric model of mortgage default, based only on information available at or before deals in that vintage were issued. For each deal, we then substitute characteristics of each mortgage in the deal into the default model, and construct a projected deal-level default rate, as a simple summary statistic for credit risk.

If ratings efficiently aggregate available information at time of issuance, this summary statistic, or other variables in the rating agency's information set, should not be systematically correlated with deal performance after conditioning on the rating (e.g. Muth, 1961; Sargent, 1987). In practice, however, projected default from the model is found to be strongly correlated with future performance of the deal, such as default rates of mortgages in the deal at different horizons, and realized losses, after controlling for the rating. (Our primary measure of ratings is the fraction of the deal which does not attract a AAA rating, also known as the level of AAA subordination or the AAA attachment point). Furthermore, in a "horse race", this summary statistic is significantly more correlated with performance than are credit ratings themselves. These findings are present over the entire sample period, but are more pronounced for deals issued during the peak of the mortgage boom, between 2005:Q1 and 2007:Q2. In addition, a higher model default rate also predicts higher ex-post credit rating downgrades. These results hold both cross-sectionally (i.e. controlling for time fixed effects and just considering variation across deals issued around the same time), in the time series, and when estimating vintage-by-vintage regressions.

The second part of our analysis studies the determinants of MBS credit ratings. Ratings are found to be correlated with credit risk and other fundamentals in expected directions. For example, less diversified deals (with a higher geographic concentration of loans) have higher average subordination; this is consistent with expectations, since the correlation of losses across loans is likely to be higher for such deals. In the time-series, ratings conditional on default risk and other deal controls are found to become more conservative during the first part of our sample (2001-04), but then decline significantly around the peak of the mortgage credit boom (2005-07). Consistent with our other results, during this latter period, risk as measured by the loan-level model increases significantly, but this is not reflected in average credit ratings, which remain roughly constant.

In addition to these results, we find several other results regarding the determinants of ratings and predictors of MBS performance. Deals with a high fraction of low-documentation mortgages are downgraded more often and have higher ex-post default rates, even conditional on both the initial rating and the prediction of the historical econometric model. This suggests that such mortgages became structurally progressively riskier over the sample period than historical performance would have suggested, consistent with the arguments of Rajan, Seru and Vig (2009). Consistent with Benmelech and Dlugosz (2009) deals rated by a single credit rating agency are also found to perform worse ex-post than their rating would suggest, however we note that such deals make up only a tiny fraction, around 1 percent, of our sample.

The evidence in this paper relates to an active current debate about the credit rating process, the role of rating agencies in the crisis, and the appropriate market structure of the credit rating industry. On one hand, CRAs argue in their defense that they repeatedly warned of lower underwriting standards and higher risks in the subprime market, and that credit ratings became progressively more conservative, reflecting these assessments (Kanef, 2007).[1] On the other hand, critics claim that ratings were inflated during the mortgage boom, either due to innocent mistakes in modeling, or explicit agency conflicts due for example to the fact that CRAs are paid by the financial institution issuing the deal rather than by investors. Relating to agency conflicts, Jerry Fons, a former Moody's executive, argues in Congressional testimony that: *"My view is that a large part of the blame can be placed on the inherent conflicts of interest found in the issuer-pays business model and rating shopping by issuers of structured securities. A drive to maintain or expand market share made the rating agencies willing participants in this shopping spree. It was also relatively easy for the major banks to play the agencies off one another because of the opacity of the structured transactions and the high potential fees earned by the winning agency."* (Fons, 2008).

Our findings contribute to a growing theoretical and empirical literature on the credit rating industry. Bolton, Freixas and Shapiro (2008), Faure-Grimaud, Peyrache and Quesada (2007), Skreta and Veldkamp (2008), Mariano (2008), and Mathis, McAndrews and Rochet (2008) present theoretical models of various aspects of incentive problems between CRAs, issuers and investors, such as the ability of rating agencies to gain or lose reputation in a dynamic setting, and the relationship between complexity and rating bias. Mathis, McAndrews and Rochet (2008) propose an alternative model for the solicitation of credit ratings which alleviates agency problems, a "platform pays" model. Boot, Milbourn and Schmeits (2006) argue that credit ratings can act as a coordinating mechanism in an environment where there are multiple equilibria.

Empirically, Coval, Jurek and Stafford (2009) describe failures of structured credit models, and document several apparent errors by rating agencies, such as an over-reliance on the assumption of rising home prices. Becker and Milbourn (2007) find evidence that the entry of Fitch into the rating industry reduced the quality of ratings of corporate bonds, consistent with a model in which competition makes sustaining a reputational equilibrium more difficult. Benmelech and Dlogosz (2008) present evidence on the rating process for collateralized debt obligations (CDOs), while Benmelech and Dlugoz (2009) find that CDOs rated only by a single

[1] In testimony to the Senate Banking Committee on September 26, 2007, Michael Kanef, Group MD of Moody's, states that: *"In response to the increase in the riskiness of loans made during the last few years and the changing economic environment, Moody's steadily increased its loss expectations and subsequent levels of credit protection on pools of subprime loans. Our loss expectations and enhancement levels rose by about 30% over the 2003 to 2006 time period."* and also that "*We provided early warnings to the market, commenting frequently and pointedly over an extended period on the deterioration in origination standards and inflated housing prices*." Kanef accounts for observed rating errors as follows: "*Along with most other market participants, however, we did not anticipate the magnitude and speed of the deterioration in mortgage quality (particularly for certain originators) or the rapid transition to restrictive lending*." Kanef cites the unexpectedly large decline in US house prices as the primary determinant of sharply higher mortgage defaults.

CRA experience larger subsequent rating downgrades. Mian and Sufi (2007) argue that increased securitization and credit availability contributed to the growth in house prices observed from 2000 to 2006.

Most closely related to our work in terms of data and methodology, Nadauld and Sherlund (2008) study in detail the relationship between MBS credit ratings and house price appreciation, using a sample of subprime MBS deals. They find that mortgages located in areas with higher house price appreciation have lower subordination. They also show that following the passage of SEC regulation reducing capital requirements for broker-dealers, those dealers disproportionately increased their purchases of mortgages from areas with high house price appreciation but lower credit quality on other dimensions. Although the focus of our paper is somewhat different, we consider house price appreciation as one of the covariates in our loan-level model. We find that higher house price appreciation prior to mortgage origination is associated with lower ex-post delinquency rates, reflecting the persistence of house price growth, which in turn leads to lower subordination rates, consistent with the results of Nadauld and Sherlund (2008).

The rest of this paper proceeds as follows. Section 2 provides background institutional information about the securitization of non-agency securities. Section 3 explains the construction of our dataset, and presents stylized facts based on our data. Section 4 reviews the theory literature in more detail, and develops testable hypotheses. It then explains the empirical strategy used in the paper to test these hypotheses, including the construction of a number of new variables. Section 5 presents estimates from our loan-level econometric model. Section 6 presents evidence of the informational content of ratings for deal performance. Section 7 studies the determinants of ratings. Section 8 concludes.

2. Background: non-agency securitization market

This section provides a short introduction to the non-agency securitization market, and the methodology used by CRAs to rate non-agency deals over our sample period. For more details, the reader is referred to Ashcraft and Schuermann (2008) and Gorton (2008).

2.1 Overview of non-agency MBS

The non-agency market consists of MBS securitized through financial institutions other than the GSEs Fannie Mae, Freddie Mac and Ginnie Mae. Investors in non-agency MBS are exposed to credit risk relating to fluctuations in default rates on mortgages underlying the deal (in the agency market this credit risk is assumed by GSEs, rather than being borne by private-sector investors). The typical subprime trust has several structural features designed to protect investors from credit losses on the underlying mortgage loans, including (i) subordination, (ii) excess spread, (iii) shifting interest, (iv) performance triggers, (v) external forms of credit enhancement such as interest rate swaps and bond insurance. We briefly discuss each of these forms of credit enhancement in turn below.

Subordination. The distribution of losses on the mortgage pool is typically tranched into different classes. In particular, losses on the mortgage loan pool are applied first to the most junior class of investors until the principal balance of that class is completely exhausted. At that point, losses are allocated to the most junior class remaining, and so on. Figure 2 presents a simple schematic of how individual mortgages are pooled into a tax-advantaged special purpose vehicle known as a REMIC trust, and then tranched into a senior-subordinated structure.

[INSERT FIGURE 2 HERE]

The most junior class of a securitization is referred to as the equity tranche. In the case of subprime mortgage loans, the equity tranche is typically created through over-collateralization, which means that the principal balance of the mortgage loans exceeds the sum of principal balances of all the debt issued by the trust. This is an important form of credit enhancement that is funded by the arranger in part through the premium it receives on offered securities. Overcollateralization is used to reduce the exposure of debt investors to loss on the pool mortgage loans.

A small part of the capital structure of the trust is made up of the mezzanine class of debt securities, which are next in line to absorb losses once the equity tranche is exhausted. This class of securities typically has several tranches with credit ratings that vary between AA and B. With greater risk comes greater return, as these securities pay the highest interest rates to investors. The lion's share of the capital structure is always funded by the senior class of debt securities, which are last in line to absorb losses. The face value of the senior securities is protected both by the equity tranche, and the width of the mezzanine class. Senior securities generally have the highest rating, and since they are last in line (to absorb losses), pay the lowest interest rates to investors.

Excess spread. Subordination is not the only protection that senior and mezzanine tranche investors have against loss. The weighted average coupon from the mortgage loan will typically be larger than fees to the servicers, net payments to the swap counterparty, and the weighted average coupon on debt securities issued by the trust. This difference is referred to as excess spread, which is used to absorb credit losses on the mortgage loans, with the remainder distributed each month to the owners of the equity tranche. The amount of credit enhancement provided by excess spread depends on both the severity as well as the timing of losses. The amount of excess spread varies by deal, but averaged about 2.5 percent during the peak of the boom. Excess spread makes up a larger fraction of the credit protection for junior tranches, which are first to absorb losses, than for the AAA tranches, which are protected by a larger subordination buffer.

Shifting interest. Senior investors are also protected by the practice of shifting interest, which requires that all principal payments to be applied to senior notes over a specified period of time (usually the first 36 months) before being paid to mezzanine bondholders. During this time, known as the "lockout period," mezzanine bondholders receive only the coupon on their notes. As the principal of senior notes is paid down, the ratio of the senior class to the balance of the entire deal (senior interest) decreases during the first couple years, hence the term "shifting interest". The amount of subordination (alternatively, credit enhancement) for the senior class increases over time because the amount of senior bonds outstanding is smaller relative to the amount outstanding for mezzanine bonds.

After the lockout period, subject to passing performance tests,[2] principal is applied to mezzanine notes from the bottom of the capital structure up until target levels of subordination are reached (usually twice the initial subordination, as a percent of current balance). In addition to protecting senior note holders, the purpose of the shifting interest mechanism is to adjust subordination across the capital structure after sufficient seasoning. Also, the release of overcollateralization and pay-down of mezzanine notes reduces the average life of these bonds and the interest costs of the securitization.

2.2 The rating process

A credit rating by a CRA represents an overall assessment and opinion of a debt obligor's creditworthiness and is thus meant to reflect only credit or default risk. Credit ratings are intended to be comparable across different types of fixed income instruments. In the words of a Moody's presentation (Moody's, 2004), *"[t]he comparability of these opinions holds regardless of the country of the issuer, is industry, asset class, or type of fixed-income debt."* A recent S&P document states "*[o]ur ratings represent a uniform measure of credit quality globally and across all types of debt instruments. In other words, an 'AAA' rated corporate bond should exhibit the same degree of credit quality as an 'AAA' rated securitized issue.*" (Standard and Poors, 2007, p.4). Despite these intentions, academic research has uncovered evidence of significant differences in expected loss rates for AAA securities across different instruments. See Nickell, Perraudin, and Varvotto (2000) for evidence across countries of domicile and industries for

[2] There are two types of performance tests in subprime deals, one testing the deal's cumulative losses against a loss schedule, and another test for 60+ day delinquencies.

corporate bond ratings, and CGFS (2005) and Mason and Rosner (2007) for differences between corporate bonds and structured products.

Rating agencies differ about what exactly is assessed. Whereas Fitch and S&P evaluate an obligor's overall capacity to meet its financial obligation, and hence is best through of as an estimate of probability of default, Moody's assessment incorporates some judgment of recovery in the event of loss. In the argot of credit risk management, S&P measures PD (probability of default) while Moody's measure is somewhat closer to EL (expected loss) (BCBS, 2000).[3] Interestingly, these differences seem to remain for structured products. In describing their ratings criteria and methodology for structured products, S&P states: "*[w]e base our ratings framework on the likelihood of default rather than expected loss or loss given default. In other words, our ratings at the rated instrument level don't incorporate any analysis or opinion on post-default recovery prospects*." (S&P, 2007, p. 3) By contrast, Fitch incorporates some measure of expected recovery into their structured product ratings.[4]

Credit ratings issued by the agencies typically represent an unconditional view, sometimes called "cycle-neutral" or "through-the-cycle:" the rating agency's own description of their rating methodology broadly supports this view. Substantial evidence suggests that credit rating changes, including changes to default, exhibit pro-cyclical or systematic variation (see Ashcraft and Schuermann, 2008 for references).

The rating process for can be split into two steps: (i) estimation of a loss distribution, and (ii) simulation of cash flows. With a loss distribution in hand, it is straightforward to measure the amount of credit enhancement necessary for a tranche to attain a given credit rating. Credit enhancement (CE) is simply the amount of loss on underlying collateral that can be absorbed before the tranche absorbs any loss. When a credit rating is associated with the probability of default, the amount of credit enhancement is simply the level of loss CE such that the probability that loss is higher than CE is equal to the probability of default.

In the first step of the rating process, the rating agency estimates the loss distribution associated with a given pool of collateral. The mean of the loss distribution is measured through the construction of a baseline frequency of foreclosure and loss severity for each loan that depends on the characteristics of the loan and local area economic conditions. The distribution of losses is constructed by estimating the sensitivity of losses to local area economic conditions for each mortgage loan, and then simulating future paths of local area economic conditions.

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[3] Specifically, EL = PD×LGD, where LGD is loss given default. However, given the paucity of LGD data, little variation in EL exists at the obligor (as opposed to instrument) level can be attributed to variation in LGD making the distinction between the agencies modest at best.

[4] See http://www.fitchratings.com/corporate/fitchResources.cfm?detail=1&rd_file=intro#rtng_actn.

In order to construct the baseline, the rating agency uses historical data in order to estimate the likely sensitivity of the frequency of foreclosure and severity of loss to underwriting characteristics of the loan, the experience of the originator and servicer, and local area and national economic conditions. Most of the agencies claim to rely in part on loan-level data from *LoanPerformance* over 1992-2000 in order to estimate these relationships.

The key loan underwriting characteristics include combined loan-to-value ratio (CLTV), consumer credit score (FICO), loan maturity (15 years, 30 years, 40 years, etc), the mortgage interest rate, and whether the loan is fixed-rate (FRM) or adjustable-rate (ARM), the property type (single-family, townhouse, condo, multi-family), the home value, documentation of income and assets, loan purpose (purchase, term refinance, cash-out refinance), owner occupancy (owner-occupied, investor), and the presence of mortgage insurance. The key originator and servicer adjustments include past performance of the originator's loans, underwriting guidelines of the mortgage loans and adherence to them, loan marketing practices, credit checks made on borrowers, appraisal standards, experience in origination of mortgages, collection practices and loan modification and liquidation practices.

The rating agency will typically adjust this baseline for current local area economic conditions like the unemployment rate, interest rates, and home price appreciation. The agencies are quite opaque about this relationship, and for some reason do not illustrate the impact of changes in local area economic conditions on credit enhancement in their public rating criteria.

In order to simulate the loss distribution, the rating agency needs to estimate the sensitivity of losses to local area economic conditions. Fitch tackles this problem by breaking out actual losses on mortgage loans into independent national and state components for each quarter. The sensitivity of losses to each factor is equal to one by construction. The final step is to fix a distribution for each of these components, and then simulate the loss distribution of the mortgage pool using random draws from the distribution of state and national components of unexpected loss.[5]

The second part of the rating process involves simulating the cash flows of the structure in order to determine how much credit excess spread will receive towards meeting the required credit enhancement. In this section, we briefly describe how the rating agencies measure this credit attributed to excess spread, focusing on subprime RMBS. The key inputs into the cash flow

[5] Note that Fitch actually simulates the frequency of foreclosure and loss severity separately, but the discussion here focuses on the product (expected loss) for simplicity. Each of the national and state components is likely transformed by subtracting the mean and dividing by the standard deviation, so that the distribution converges to a standard normal distribution. This permits the agency to use a two-factor copula model in order to simulate the loss distribution. Note that the sensitivity of losses to the normalized component would be equal to the inverse of the standard deviation of the actual component.

analysis involve the credit enhancement for given credit rating, the timing of these losses, prepayment rates, interest rates and index mismatches, trigger events, weighted average loan rate decrease, prepayment penalties, pre-funding accounts, and swaps, caps, and other derivatives.

The first input to the analysis is amount of losses on collateral that a tranche with a given rating would be able to withstand without sustaining a loss, which corresponds to the required credit enhancement implied from the loss distribution. Note that better credit ratings are associated with higher levels credit enhancement, and thus are associated with a higher level of expected loss on the underlying collateral.

2.3 Review of theory literature

In this section we review in more detail three recent theoretical papers on CRAs, and highlight a number of theoretical predictions identified by this work regarding the determinants of equilibrium rating inflation.

Bolton, Freixas and Shapiro (2008) model a single securities issuer who obtains ratings from one or multiple CRAs. Each of the CRAs has some private signal about the quality of the security. The CRA in each case can choose to truthfully report their signal to investors, or to lie, and submit an overly optimistic report about the quality of the security. The CRA faces exogenous reputation costs if an untruthful report is observed by investors ex-post. In order to generate rating inflation in equilibrium, Bolton et al assume that a fraction of investors are naïve, and do not reconstruct the average expected rating bias, taking into account the incentives of the CRA.

Bolton, Freixas and Shapiro generate several testable predictions about the determinants of rating inflation. First, the presence of multiple CRAs, rather than a monopolist rating agency, generates more rating bias, in part due to a “shopping” effect. Namely, the issuer has the opportunity to purchase multiple ratings but reveal only favorable ones. This in turn provides incentives for CRAs to provide a more favorable report, to avoid losing market share. (This appears consistent with the empirical results of Becker and Milbourne (2008), who find that the entry of Fitch in the corporate bond market generated an erosion in standards in the ratings provided by Moody’s and S&P.) Second, bias is increasing in the fraction of “naïve” investors. Third, bias is unsurprisingly larger when the reputation costs from investor discovery of bias are smaller. This might be the case for example if the future market size is small relative to the current market size.

The role of reputation is further explored in Mathis, McAndrews and Rochet (2008), which studies an infinitely repeated game in which the rating agency may be of two types. An honest rating agency always reports their signal of the security’s quality correctly, while a dishonest CRA can choose to give an incorrect report. Mathis et al show that when the fraction of CRA revenue from rating the security class in question is large enough, the rating agency of the dishonest type will always lie with positive probability in equilibrium. They show that for some parameters an equilibrium with "reputation cycles" is possible. When the CRAs reputation is poor, there is no inflation and the CRA builds reputation. Over time, investor optimism increases, and the incentives for the CRA to inflate ratings increases. Eventually, CRA rating bias is uncovered, and investors become more pessimistic. In stylized terms, the Mathis model appears to describe the pattern of structured securities issuance during the mortgage boom that preceeded the subprime crisis. During this period, the fraction of CRA income earned from rating structured securities was extremely high, which in the Mathis et al framework makes rating inflation more likely. We thus test whether rating standards fell in the period leading up to the peak of issuance of non-agency securities in 2005-07.

Finally, Skreta and Veldkamp (2008) study the relationship between asset complexity and equilibrium rating inflation. They model a single asset issuer who can choose to selectively request and disclose ratings from multiple CRAs. Complexity in their framework is defined as the residual uncertainty in fundamental asset value conditional on the signal of the rating agency. Thus, it could also be interepreted as a measure of disagreement across CRAs as to the fundamental value of the asset. When complexity is low, the CRA reports are very similar, and . When complexity is extremely high, CRA reports are entirely uninformative. Numerically Skreta and Veldkamp show in the intermediate region that rating shopping and rating inflation is increasing in the degree of complexity of the security being rated.

3. Data and stylized facts

We analyze the rating of subprime and non-agency MBS deals using a dataset that combines security level information from Bloomberg and ABSNet, and loan level data from LoanPerformance. This dataset covers a large fraction of the population of issued securities in this market. ABSNet and Bloomberg contain information on the characteristics of nearly all nonagency structured finance securities. LoanPerformance contains loan-level information for around 90% of nonagency deals since 2004, with a somewhat lower coverage prior to that.

3.1 Dataset construction

ABSNet and Bloomberg are used to provide information on the structure of each non-agency deal, including the original credit rating, the security's original face value, and other features, such as whether it is interest only, principal only, exchangeable and so on. LoanPerformance provides loan-level information on the characteristics and performance of each individual mortgage underlying the MBS deal. Our sample is constructed by identifying all active deals in Bloomberg for which each pool in the deal can be matched with loan-level data in the non-prime LoanPerformance dataset.

For each deal, we calculate the level of subordination below different classes, also known as the "attachment point" of different classes. In our analysis, we focus on the fraction of the face value of the deal that is junior to the AAA-rated A-Class securities. Deals whose mortgages have higher expected default rates also require more subordination, in order for the A-Class securities to be appropriately rated AAA. The AAA attachment point is calculated for each deal as follows:

$$SUBORDINATION\ \ below\ AAA = \frac{(1 - \Sigma\, face\ value\ of\ AAA - rated\ securities)}{\Sigma\, Face\ value\ of\ mortgages\ underlying\ deal}$$

When summing the face value of all AAA securities we carefully clean the data to drop tranches that would otherwise lead to double-counting (e.g. interest-only tranches that list a nominal principal balance). We also identify deals with external bond insurance, since the presence of insurance will reduce the level of internal required credit enhancement through subordination, other things equal.

For purposes of this draft, we exclude deals including payment option ARMs, also known as negative amortization mortgages, from our analysis. This is because the cash flow structures of these mortgages are quite different from other loan types, with low initial payments that increase sharply once the mortgage recasts, and because there is a relatively short history on these mortgages in LoanPerformance. (We plan to include an analysis of these deals in the next version of the paper.)

3.1 Stylized facts

Our final dataset consists of information on the structure of 3,001 residential non-agency subprime and Alt-A deals, consisting of 57,995 individual securities. Each deal is matched with loan-level data on the characteristics and payment history of the mortgage collateral underlying each deal.

The rapid growth and subsequent decline of deal flow in the subprime and Alt-A MBS market, based on our data, is plotted in Figure 3. Issuance grew rapidly between 2002 and 2006. At the market peak in 2006, around 250 new deals were being issued each quarter in subprime and Alt-A combined (or around $200bn of face value). This issuance declined rapidly starting in the second half of 2007, with virtually no new deals being issued in 2008.

[INSERT FIGURE 3]

Summary statistics of the deals in our sample are summarized in Table 1. The average deal has face value of $750m, with the subprime deals on average being somewhat larger than Alt-A deals. Alt-A deals are generally backed by higher-quality collateral than subprime deals (i.e. mortgages with a lower expected probability of default). Reflecting this, a larger fraction of the securities issued in Alt-A deals are rated AAA; 94% compared to 82% for the subprime deals. These figures match closely with average subordination rates reported from other sources (e.g. Ashcraft and Schuermann, 2008; Gorton, 2008).

[INSERT TABLE 1 HERE]

Table 2 presents summary statistics for the mortgage collateral underlying these deals. On average, each subprime deal is backed by 5,553 individual mortgages, while each Alt-A deal is backed by 2,170 loans. This difference reflects the larger principal values for Alt-A loans and the larger number of junior lien mortgages in the subprime deals. Consistent with conventional industry wisdom, Table 2 shows that Alt-A deals are made up of mortgages to borrowers with higher average FICO scores and lower loan-to-valuation ratios, but have a higher fraction of "exotic" mortgages, such as interest only mortgages and low- or no-documentation mortgages.

[INSERT TABLE 2 HERE]

Table 3 presents time series patterns in the key variables. As the table shows, the fraction of interest only and low- or no-documentation loans increases significantly over the sample period.

[INSERT TABLE 3 HERE]

3.1 Stylized facts about the rating process

We identify which credit rating agencies (CRAs) provided solicited ratings for each of the deals in our sample amongst the three active CRAs over our sample period: Moody's, S&P and Fitch. In Figure 4 below we plot time-series trends in the fraction of deals that are rated by one, two or all three CRAs, by year-quarter between 2000:Q1 and 2008:Q1.

[INSERT FIGURE 4]

The first striking fact in Figure 4 is that virtually all the deals in our sample are rated by at least two of the three primary CRAs. In the Alt-A market, where mortgage borrowers generally have better underwriting characteristics, two ratings is the norm. Early in the sample, three ratings is the norm in the subprime market, although this declines substantially over the sample period, as shown in the Figure.

Next, we compute the market share of each CRA in both the subprime and Alt-A markets. These are plotted in Figure 5. Becker and Milbourn (2008) argue that in the corporate bond market, the entry of Fitch was associated with a decline in rating standards by Moody's and

S&P. However, in the structured credit market this dynamic does not seem to be important over our sample period; in contrast, Fitch's market share trends downwards in both submarkets over the sample, particularly for Alt-A. This decline may reflect the increasing importance of CDO investors; standard practice was for CRAs rating CDOs to penalize MBS securities in the deal not initially rated by the CDO rater. This may have penalized Fitch, who did not have a large market share in rating CDOs.

[INSERT FIGURE 5]

3.2 Trends in credit enhancement

Table 1 presents basic summary statistics about trends in credit ratings and other types of credit enhancement, namely excess spread at origination and bond insurance. This information is also presented graphically in Figures 6 and 7. Figure 7 presents a graph of the time-series trends in the level of subordination on subprime and Alt-A deals over the period 2000-2008.

[INSERT FIGURE 6 HERE]

Figure 7 shows that, based simply on the fraction of securities rated AAA, the rating of subprime RMBS deals did indeed become more conservative over this sample period. Namely, over time a lower fraction of the face value of the claims on subprime deals was awarded a AAA rating. There is a small upward slope in subordination for Alt-A deals, although it is much less pronounced than for the subprime market.

There are several reasons why this trend in unconditional subordination may have occurred. One is simply that there was substitution between subordination and other forms of credit enhancement. Figure 7 plots trends in the average amount of external bond insurance on the deals, and the average level of excess spread at origination (measured the difference between the total dollar value of coupon payments promised to securityholders and the total interest payments on mortgages underlying the deal, divided by the face value of the deal). The figure does indeed show a secular decline in both these alternative forms of credit enhancement, partially offsetting for the increase in subordination documented in Figure 6.

[INSERT FIGURE 7 HERE]

4. Empirical strategy

Our empirical analysis is based on both an "ex-ante" analysis of the determinants of ratings, and an "ex-post" analysis of the relationship between ratings and deal performance. Our primary measure of performance is the weighted fraction of mortgages in the deal that are in default, defined as 90+ days delinquent, prepaid with loss or REO at different horizons after deal issuance. Realized losses and rating downgrades are also used as alternative measures of deal performance. We analyze how that this fraction of mortgage defaults, as well as rating downgrades and realized losses, are related to initial ratings on the deal, as well as other covariates. Ex-ante, we analyze factors that determine credit ratings, and study variation in ratings conditional on fundamentals.

Both parts of our analysis make use of a simple benchmark default model. For each deal, this model is estimated only using data available to CRAs at the time the deal was issued. The structure of this model is described in more detail in the following section. The purpose of this model is to construct a simple summary statistic for the credit risk of each deal. The model excludes a variety of features of the rating process, for example ratings are based on a set of simulated paths for interest rates and house prices, and explicit transitions between different states of delinquency. Ratings also take into account variables not included in the model, such as the quality of individual originators. In short, the model is not intended to be a comprehensive or "best practice" model of credit risk; in fact, to the contrary, it is an intentionally simple structure that includes only basic underwriting data that was also available to rating agencies.

Our ex-ante analysis first studies the determinants of initial credit ratings. We analyze whether ratings are related to fundamentals in the expected directions. For example, we expect that subordination is: (i) increasing in projected loss rates on the mortgage collateral; (ii) increasing in the geographic concentration of loans; (iii) decreasing in the strength of other types of credit enhancement, namely greater excess spread at origination and the presence of external bond insurance.

After controlling for these factors, we then study time-series trends in the level of subordination. Mathis, McAndrews and Rochet (2008) predict that credit ratings should be subject to "reputation cycles", in which ratings are inflated during periods where CRAs have strong incentives to relax standards in order to increase current revenue. This is eventually discovered by investors, leading to a period where ratings are conservative as the CRA attempts to recover reputational capital. We thus study time-series variation in ratings conditional on the fundamentals identified in Hypothesis 3, to determine the presence or otherwise of time-series fluctuations that would be consistent with reputation cycles.

Hypothesis 1 (Rating stability): *Ratings remain constant through time, after controlling for the level of credit risk and other structural features of the deal (e.g. excess spread, external bond insurance).*

In our ex-post analysis, we test whether non-agency credit ratings efficiently aggregate information that was available to the rating agency about the credit risk of the deal. Muth (1961) and Sargent (1987) show that a rational forecast of a future outcome is a sufficient statistic for the forecaster's information set about that predicted outcome at the time the forecast is made. In other words, after controlling for the credit rating, other prior information available at deal issuance, like borrowers' average FICO scores, or the fraction of low-documentation loans, should not systematically have power for forecasting future losses, since if it did, that additional information should have been incorporated into the credit rating.

In particular, in our empirical work, we build several simple loan-level econometric models of mortgage delinquency using only information available at or before the deal is issued. (For example, for each deal vintage we estimate the model recursively using only data available at the time the deal was rated). We then test whether these models have predictive power for ex-post mortgage defaults, even after controlling for the credit rating on the deal.

Hypothesis 2 (Informational Efficiency)*: All relevant information available at deal issuance that helps forecast mortgage losses should be reflected in the rating. Thus, this information should not systematically forecast deal level loss rates, after conditioning on the rating.*

Finally as discussed in Section 2, a number of recent theory papers, including Bolton, Freixas and Shapiro (2008) and Skreta and Veldkamp (2008) present a model of *rating shopping*, in which issuers selectively report only favorable ratings. Although testing for rating shopping is not the primary purpose of our paper, we do study how rating "strategy" (that is, the combination of CRAs that rate the deal) is related to both the amount of initial subordination below AAA required by the rating agencies, as well as ex-post losses conditional on fundamentals. We note however, that significance of these variables would provide only suggestive evidence of rating shopping, since the choice of CRAs is endogenous, and thus any correlations between it and other outcomes could reflect selection bias rather than the presence of shopping.

5. Loan-level regressions

In table 5, we present estimates of a loan level econometric model of mortgage defaults. The model presented in the table is based on a 10% sample of the entire LoanPerformance database, although in our empirical analysis, we estimate the model recursively over different subsamples of the data. This LoanPeformance data is merged with OFHEO house price data at either the state or MSA level (depending on whether the property underlying the loan is located in an MSA), as well as the state unemployment rate.

The dependent variable in our loan level regressions is a dummy equal to 1 if the mortgage is 90+ days delinquent, REO or prepaid with loss one year after origination, and zero otherwise. Robust standard errors are clustered at the level of the issuer of the deal into which the mortgage was sold. Model estimates are adjusted to reflect marginal effects of changes in each right-hand side variable on the probability of default.

[INSERT TABLE 5 HERE]

The variables included in the model include macroeconomic data and the key underwriting variables supplied in the LoanPerformance database. The model is similar in many respects to the logistic regressions of nonagency mortgage defaults in Demyanyk and Van Hemert (2009), and also shares some features with Haughwout, Peach and Tracy (2008). Key underwriting variables included in the model include the borrower's FICO score, the combined loan-to-valuation ratio summing all mortgage liens, dummies for the type of loan (FRM, ARM, interest only, balloon loan), the borrower debt-payments to income ratio (DTI), level of documentation of borrower income (full, partial or none), a dummy for whether the borrower is an investor rather than an owner occupier.

We also control for the level of local house price appreciation (based on the MSA-level OFHEO index), and find that 12-month trailing HPA is significantly negatively correlated with *subsequent* mortgage default. (Note this is a somewhat different result from previous research, that studies the effect of ex-post, not ex-ante, HPA as a determinant of mortgage default). The explanation for this result is that HPA growth is highly positively autocorrelated (Case and Shiller, 1987). Thus, high HPA today on average forecasts high future HPA, which in turn generates higher borrower equity, discouraging default and making it easier for borrowers to refinance into a low-interest-rate prime mortgage.

To construct a projected delinquency rate for each deal in our sample, we estimate this model recursively for each deal vintage from 2001 to 2007. In each case, we re-estimate the model fourteen times, in each case utilizing only information that was available to the CRAs at the beginning of the year in question. We then substitute the features of each mortgage in the deal in question into this econometric default model, and calculate a projected delinquency rate. We the take the weighted average of these projected delinquency rates for all mortgages in the deal (weighted by loan size), thereby aggregating the projected delinquency rate up to the deal level. This is our key measure of the underlying credit quality of the deal, for the purposes of the deal-level regressions.

Figure 8 plots the projected 12-month post delinquency rate from this baseline model over time. The x-axis of this figure is the year-quarter that the deal was issued. Also plotted on this figure is the ex-post realized 12-month average deal default rate by year-quarter. The model generally does a good job of projecting mortgage defaults over time, although it significantly lags the actual increase in subprime mortgage delinquencies observed beginning in the 2006 vintage. This divergence between projected and actual default primarily reflects the sharp deterioration in the US housing market starting in 2006.

[INSERT FIGURE 8 HERE]

6. Determinants of credit ratings

The first part of our empirical work is a study of the determinants of non-agency MBS credit ratings. We study the relationship between assigned ratings and credit risk, as measured by the projected default rate from the loan level model, as well as other fundamentals, namely the level of other types of credit enhancement, including: a dummy for the presence of bond insurance, the fraction of the deal with insurance, the weighted average coupon rate and interest rate, and a measure of the geographic diversification of loans in the deal, namely the sum of the squared shares of loans in each deal from each of the 50 US states.

Table 8 below presents baseline results for the deal level regression. The Table shows that the fundamental variables are indeed correlated in the expected way with the amount of required subordination on the deal. Most strikingly, the projected 12 month delinquency rate, which is a summary statistic based on all the underlying loan-level data, is positive as expected, and statistically significant at any conventional level. Other variables generally also have the expected sign. For example, greater geographic dispersion is correlated with lower subordination on the deal, which we would expect since it implies that the variance of credit losses will be smaller.

[INSERT TABLE 8 HERE]

The model in Table 5 also includes year-quarter dummies. In Figure 9, we present time-series trends in the unconditional level of subordination on subprime and Alt-A deals, as well as the level of subordination after controlling for fundamentals as listed in Table 5. Trends in conditional subordination are simply the time-series of these year quarter dummies from the regressions in Table 5.

Looking at these two figures, we note that, controlling for credit risk, there is significant time variation in conditional subordination levels for both subprime and Alt-A deals. During the first part of the sample, between 2001 and 2004, subprime ratings become significantly more conservative, both unconditionally and conditional on the fundamentals in Table 5. This suggests that CRAs were becoming more conservative, perhaps putting some weight on the possibility of a large fall in house prices. However, in the latter part of the sample, between 2005 and 2007, ratings conditional on risk decline by about 10 percentage points. This reflects that risk on subprime deals, as measured by the loan-level model, was increasing over this period, as shown in Figure 8, but that ratings did not become more conservative to reflect this risk. The same trend is apparent for Alt-A, but to a lesser extent. The last row of Table 5 shows the p-value from an F-test that the average rating during the "boom" period between Q1:2005 and Q2:2007 is equal to its value in Q4:2004. In three of the four columns it is possible to reject this null hypothesis at the 5% or 1% level, in the other case (for Alt-A deals after including additional aggregated loan-level covariates) the p-value is 0.116.

[INSERT FIGURE 9]

These results suggest that ratings adjust to other forms of credit enhancement in expected ways, and also that ratings are correlated with credit risk, as measured by the model-projected default rate. These results also provide prima facie evidence of time-variation in credit ratings, with a deterioration in ratings at the end of the mortgage credit boom that preceded the crisis. While this evidence is suggestive, a plausible alternative interpretation is that ratings did incorporate this observed increase in risk, but were also responding to additional offsetting information not accounted for by our simple loan-level model. To explore this in more detail, we turn to an investigation of the informational content of ratings, and in particular, a statistical test for whether the model projected default rate contains important incremental information for default that is not incorporated in ratings.

7. Determinants of deal-level mortgage default rates

The second part of our empirical analysis studies the ex-post performance of subprime and Alt-A MBS deals. Our primary measure of performance is the weighted fraction of mortgages in the deal that are in default (defined as 90+ days delinquent, prepaid with loss or real-estate owned, REO), 12 months after deal issuance. Later we also study default at other horizons, as well as realized losses and ex-post rating downgrade events.

In Table 6, we present deal-level regressions of the relationship between ex-post default, initial credit ratings measured by subordination below AAA, the projected default rate from the loan-level model, and a set of controls. The controls are the same measures of other forms of credit enhancement and deal structure included in Table 5. To conserve space, results for these controls are excluded from Table 6; however results for these variables are reported in Table 7 for several specifications.

[INSERT TABLE 6 HERE]

For each group of deals, five specifications are estimated. The first regression just includes the control variables. The R^2 in this regression is around 10%. The second and third columns add AAA subordination and the projected default rate in turn to the specification. Both variables are individually significant in these columns. However it is notable that the model-projected default measure is significantly more correlated with ex-post performance, as measured by the R^2 between the two specifications. Amongst subprime deals, including the rating causes the R^2 to increase from 0.10 to 0.30, however, including instead the model projected default rate causes the R^2 to rise by more than twice as much, from 0.10 to 0.53.

Columns 4 and 5 include both AAA subordination and the model-projected default rate in the specification. This is a direct test of Hypothesis 2, that ratings efficiently summarize the level of credit risk in the deal, and thus that the logit-model-projected default rate does not systematically predict default after conditioning on the level of subordination. As the table shows, both variables are statistically significant, although the coefficient on the credit rating variable is significantly smaller in magnitude than the model-projected default rate.

Table 7 is based on similar regressions except that it presents full results for controls and loan-level covariates for several specifications. The loan-level covariates include a set of aggregated summary statistics for each deal, as well as variables indicating which combination of credit rating agencies rate the deal. Benmelech and Dlugosz (2009) find evidence that asset-backed CDO deals rated by a single CRA experience higher ex-post credit downgrades. The inclusion of these "rating strategy" variables allows us to test a similar hypothesis in our sample. The final column of Table 7 also includes additional interactions between several of the key covariates and a "boom" variable set equal to 1 at the peak of non-agency issuance (2005-07).

[INSERT TABLE 7 HERE]

In addition to the significance of the predicted delinquency rate from the loan level model, several other ex-ante covariates are also statistically significant predictors of ex-post defaults conditional on the initial rating. In particular, in each specification, low- and no-documentation mortgages have significantly higher ex-post default rates than predicted, even after conditioning on the rating and the loan level model. One criticism of rating agencies during this period is that they relied excessively on information provided to them by the deal sponsor. issuer, and did not verify that information sufficiently carefully. Rajan, Seru and Vig (2008) presents a model and empirical evidence to argue that the composition of the pool of low-documentation mortgages became progressively worse over the sample period than historical models would have predicted, reflecting this change in credit quality. The high ex-post defaults observed here on low-documentation loans, even conditional on the output of the historical credit loss model, appears consistent with this view.

Finally, the rating strategy variables are jointly statistically significant in all but one of the specifications presented in Table 7. However, the signs of the coefficients are not always consistent across Alt-A and subprime. One striking fact is that ex-post default is unexpectedly high amongst deals rated by a single rating agency. This result is consistent with Benmelech and Dlugosz (2009), who find that amongst CDO deals, ex-post downgrades are more common amongst deals rated by a single CRA. Benmelech and Dlogosz interpret this finding as evidence of rating shopping. While this is certainly possible, we also note that deals rated by one rating agency make up a very small fraction (around 1%) of our sample, and that the results on other "rating strategy" dummies are less clear and also significantly different between the subprime and Alt-A submarkets and across specifications. Given these factors, and the fact that the choice of rating agencies on a deal is endogenous, and we do not have a good instrument for it, we are reluctant to draw firm conclusions about the interpretation of the statistical significance of these "rating strategy" variables.

In addition, the last column of Table 7 interacts a number of the aggregated loan-level covariates with a "boom" dummy variable equal to one during the defined "boom" period from Q1:2005 to Q2:2007. Notably, the magnitude of the coefficient on the ln(model-projected default rate) on the loan-level model increases during this period, although it is statistically significant over the entire sample period. This suggests that the statistical significance of the credit risk summary statistic is not just contained to the later part of the sample immediately preceeding the crisis.

Tables 8 and 9 conduct similar analysis using alternative measures of deal performance. Table 8 considers the determinants of rating downgrades, measured as the average number of notches that securities in the deal are downgraded after issuance (i.e. the same dependent variable as presented in Figure 1). Table 8 shows that, consistent with the rest of the analysis, deals with a high model-projected default rate are more likely to be downgraded by rating agencies ex-post, additional evidence that they were rated relatively too generously at origination. Remember that since our regressions include year x quarter dummies, this statement is made cross-sectionally (i.e. comparing deals issued around the same time, with different observable levels of credit risk as observed by the econometrician through the lens of the logistic default model).

[INSERT TABLE 8]

Table 9 studies how the same variables studied earlier are related to default at different horizons (a 24 month horizon, or default to date using as long a history from LoanPerformance as possible), or to realized losses. Realized losses are a sharply lagging indicator, since losses are not recognized until default is certain and the amount of the shortfall in payments can be measured precisely. And the sample size from examining 24-month defaults rather than 12-month defaults is also smaller. However, the basic finding from earlier Tables, that ratings are insufficiently sensitive to

[INSERT TABLE 9]

Finally, Table 10 presents vintage-by-vintage default regressions, equivalent to columns 2, 3 and 4 of Table 6. This Table confirms that the predictive power of the projected default rate holds in every year of the sample between 2001 and 2007. Thus, the insufficient sensitivity of ratings to credit risk is observable well before the mortgage credit boom or the onset of the crisis. Note also that the model-predicted default rate is consistently more correlated with ex-post default than is AAA subordination, based on a comparison of the R^2s across the specifications.

[INSERT TABLE 10]

8. Conclusions

This paper studies the determinants and informational content of ratings on subprime and Alt-A RMBS deals issued between 2001 and 2007. Our analysis suggests that MBS credit ratings were informative, in the sense that they were correlated with fundamental measures of credit risk and credit enhancement in expected ways, and also that they are correlated in the cross-section with ex-post deal performance.

However, we also find that ratings did not efficiently aggregate ex-ante information on credit risk on these deals, in ways that were apparent even before the crisis, and not simply due to poor shocks to fundamentals. In particular, ratings did not efficiently summarize available information on credit risk. In particular, ratings appear insufficiently sensitive to observable measures of credit risk based on underwriting characteristics of loans in the deal. In other words, conditional on the rating, deals that appear risky by this metric have higher ex-post defaults, higher ex-post realized losses, and also contain bonds that are more likely to be downgraded ex-post by rating agencies.

These differences are quantitatively important, and hold both cross-sectionally and in the time series. They also hold in vintage-by-vintage cross sectional regressions using only data from vintages observed well before the start of the subprime crisis. In the time-series, we observe that between 2005 and 2007, the height of the credit boom, credit risk as measured by the logistic model increases significantly, due in part to a decline in trailing house price appreciation (which peaked at the end of 2005). However, MBS subordination levels remained close to flat over this period, and thus became relatively less conservative conditional on risk. Our estimates suggest that ratings conditional on risk declined in the subprime market by about 10 percentage points over this period, equivalent to about half of the unconditional level of subordination on these deals over the sample period.

An additional contribution of this paper is to present additional stylized facts about the rating of nonagency MBS, and the effect of other deal characteristics on performance. For example, we find that deals with a high fraction of low-documentation loans have particularly poor ex-post performance consistent on historical data, consistent with arguments in Rajan, Seru and Vig (2008) that the composition of no-documentation borrowers evolved endogenously over the sample period in response to the pricing implied by historical models.

We also note that in several of our regressions, the combination of CRAs used to rate the deal is a significant predictor of ex-post defaults, even conditional on ratings and other covariates, perhaps consistent with the presence of rating shopping by sponsors, or other incentive problems. Given the lack of clear causality however, we remain agnostic on the extent to which shortcomings in the rating process reflect innocent errors in methodology, or explicit agency problems along the lines described above.

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Appendix A: Data dictionary
[TO INSERT: Definitions of the construction of each of the main variables of interest].

Appendix B: Dataset construction

[TO INSERT: Explain how we clean the ABSNet and Bloomberg data to construct the final dataset. Drop out particular tranche types to avoid double-counting, such as situations where there is an interest-only and principal-only tranche that both have a listed nominal principal balance].

Figure 1: Net credit rating downgrades, by vintage

This figure plots the net average negative change in MBS credit ratings on subprime and Alt-A securities by issuance vintage between Q1:2001 and Q4: 2007. The y-axis measures the average net number of notches that securities issued in the quarter indicated have been downgraded between issuance and June 2009, weighted by security original face value. [For example: a security downgraded from AA+ to A- would be recorded with a value of +5 since the security has been downgraded by five notches: AA+ to AA, AA-, A+, A, A-.] The scale is symmetric; a negative value means securities issued in a particular quarter have on average been upgraded. For securities rated by multiple credit rating agencies, the downgrade count is based on an average across agencies.

Subprime deals **Alt-A deals**

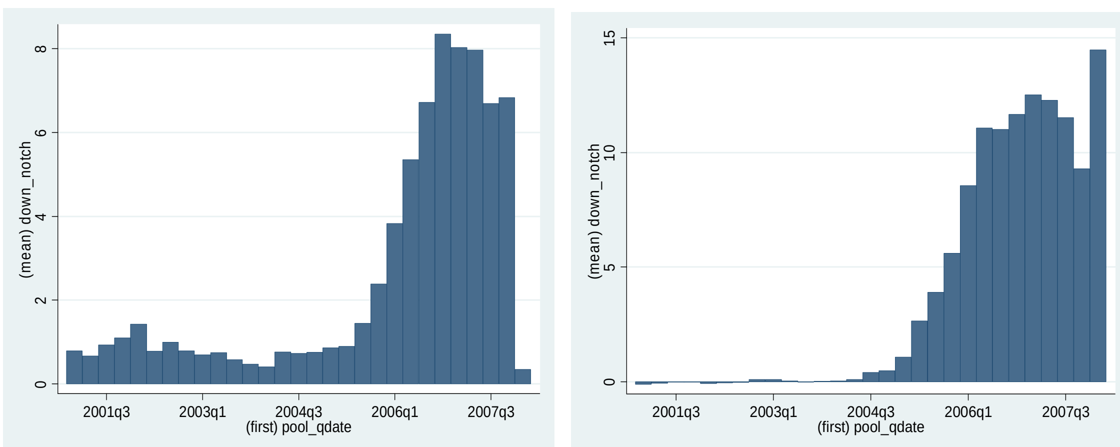


Figure 2: Structure of a non-agency MBS deal

This figure shows how individual mortgages are combined into one or more pools, which are then transferred to a special purpose vehicle called a REMIC trust. (This trust is bankruptcy remote from the issuer or the originator of the underlying mortgages). Individual securities are then issued whose cashflows derive from the pools of mortgages in the trust. These securities have a "senior-subordinated structure" which means they can be ordered in terms of seniority with respect to borrower principal payments on mortgages held in the trust. (Cashflows for an individual security may derive from a single pool, or from each of the pools in the trust). A *deal* refers to the set of securities issued against the collateral of a particular REMIC trust, while a *tranche* or *bond* refers to an individual security issued by the trust. Note that, although the diagram identifies only a single AAA security, usually there will be multiple AAA tranches, which together form the A-class of the deal.

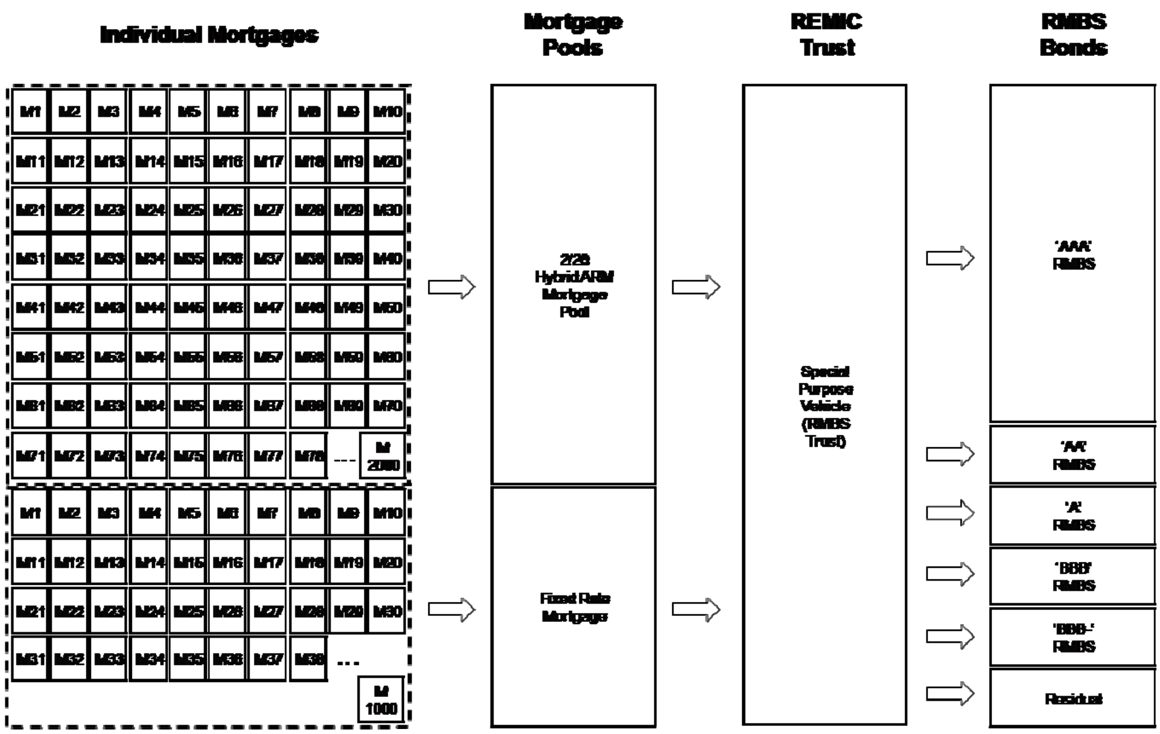


Figure 3: Evolution of Subprime and Alt-A MBS Issuance

The figure plots the number and total face value of subprime and Alt-A securities issuance by year-quarter over the period 2002-2008, based on data from Bloomberg, ABSNet and LoanPerformance. See Section 3.1 and Appendix B for more details about the construction of the deal-level dataset.

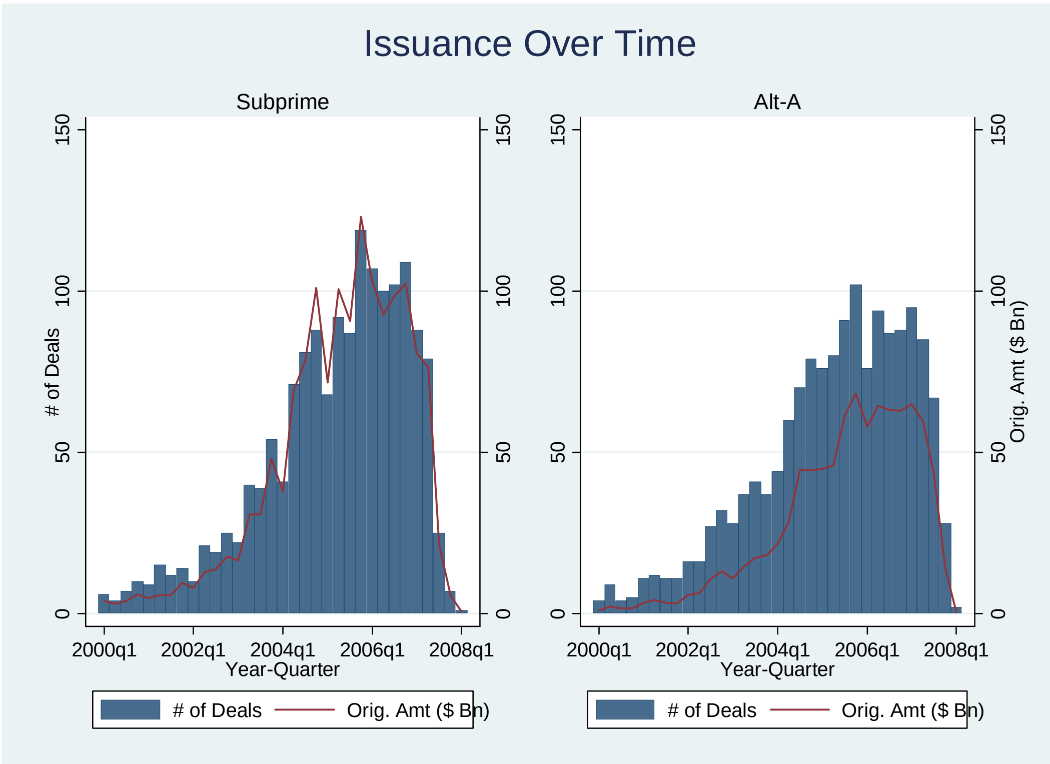


Figure 4: Evolution of the average number of ratings

This figure plots the fraction of subprime and Alt-A MBS deals rated by one, two or all three of Fitch, Moody's and S&P, by year-quarter between 2000 and 2008, based on the Bloomberg-ABSNet deal-level dataset.

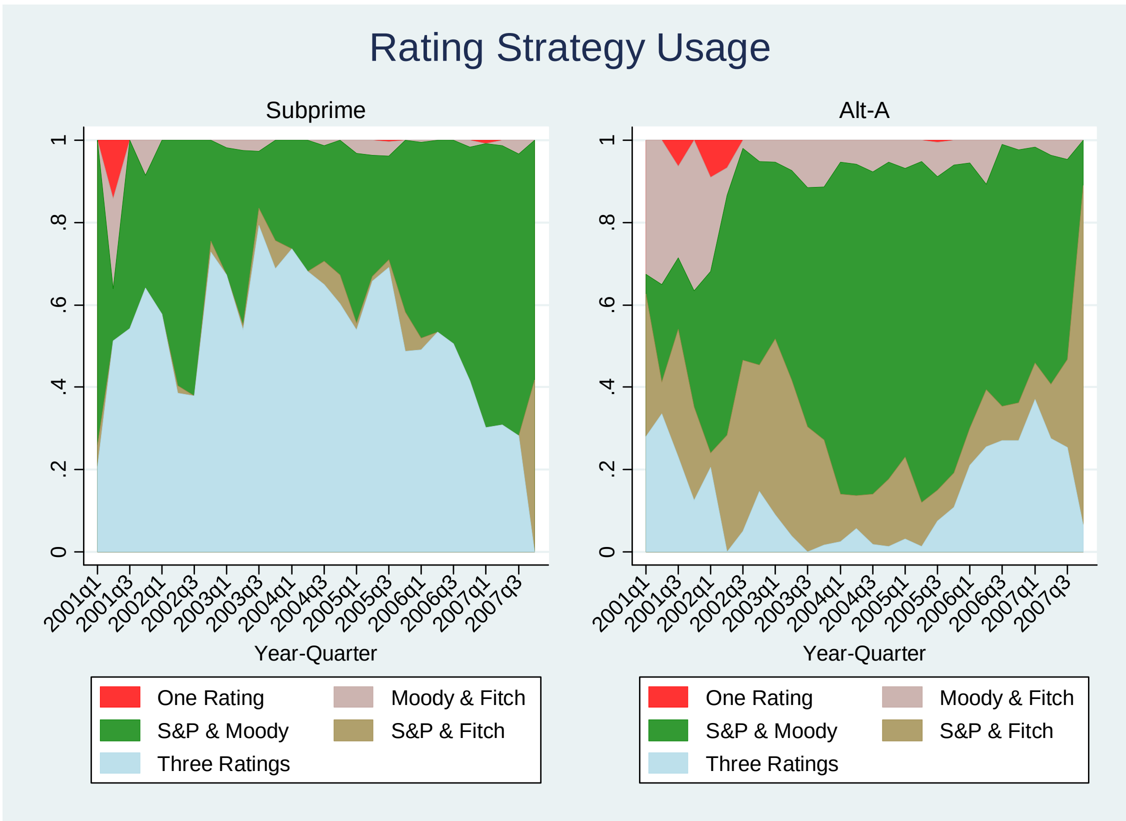


Figure 5: Market Share by Rating Agency

This figure plots the fraction of all new deals rated by Fitch, by year-quarter between 2000 and 2008, based on based on the Bloomberg-ABSNet deal-level dataset.

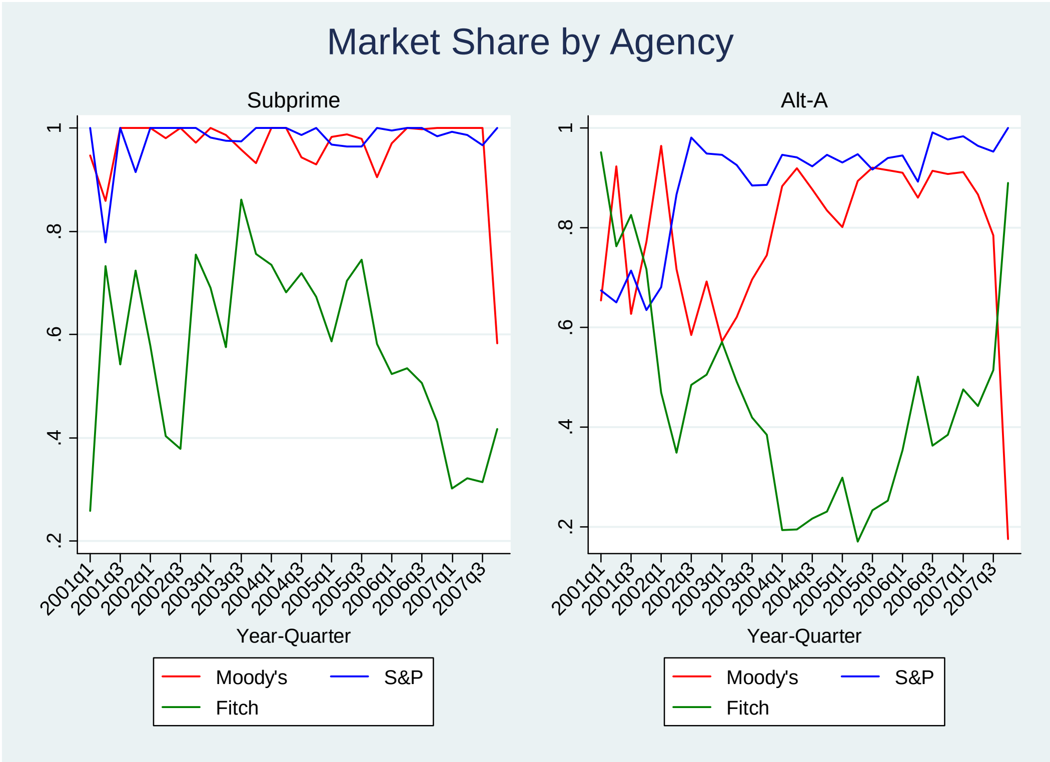


Figure 6: Evolution of subordination levels, subprime and Alt-A deals

This figure plots the average fraction of subprime and Alt-A deals that is rated below AAA, defined as subordination = 1 – [face value of AAA securities] / [face value of mortgages in the deal], by year-quarter between 2000 and 2008. Mortgage face value is taken from LoanPerformance, aggregating to the deal level. AAA face value is taken from the Bloomberg-ABSNet security-level dataset, aggregating to the deal level.

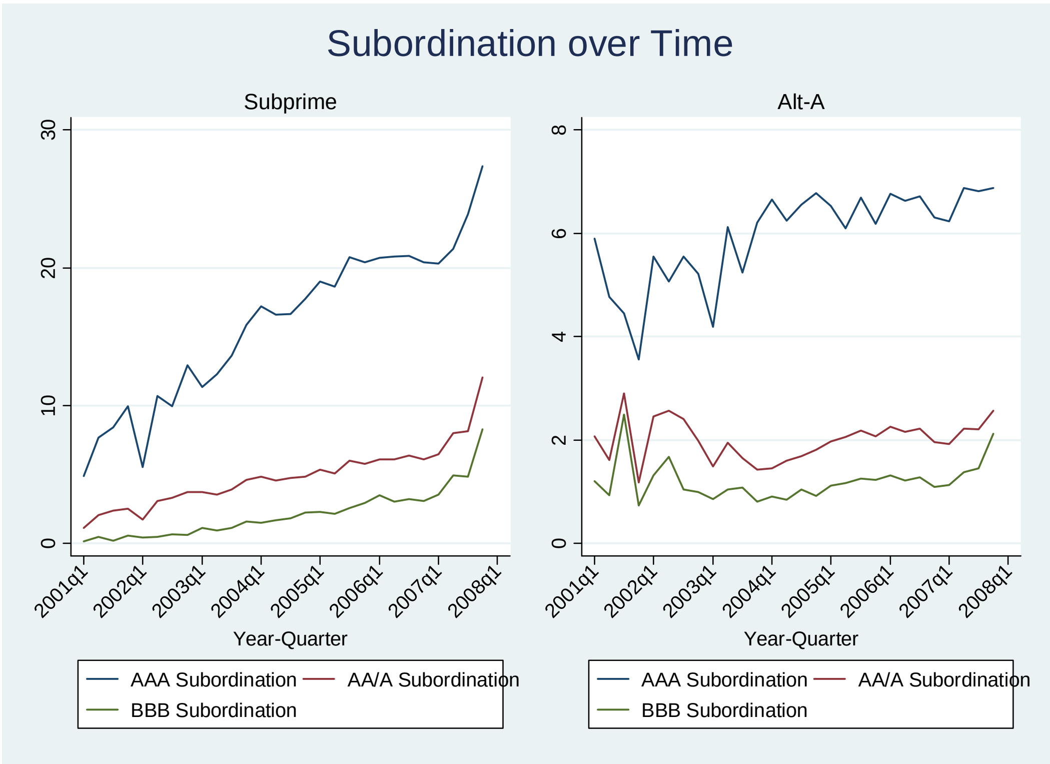


Figure 7: Evolution of excess spread and bond insurance, 2001-07

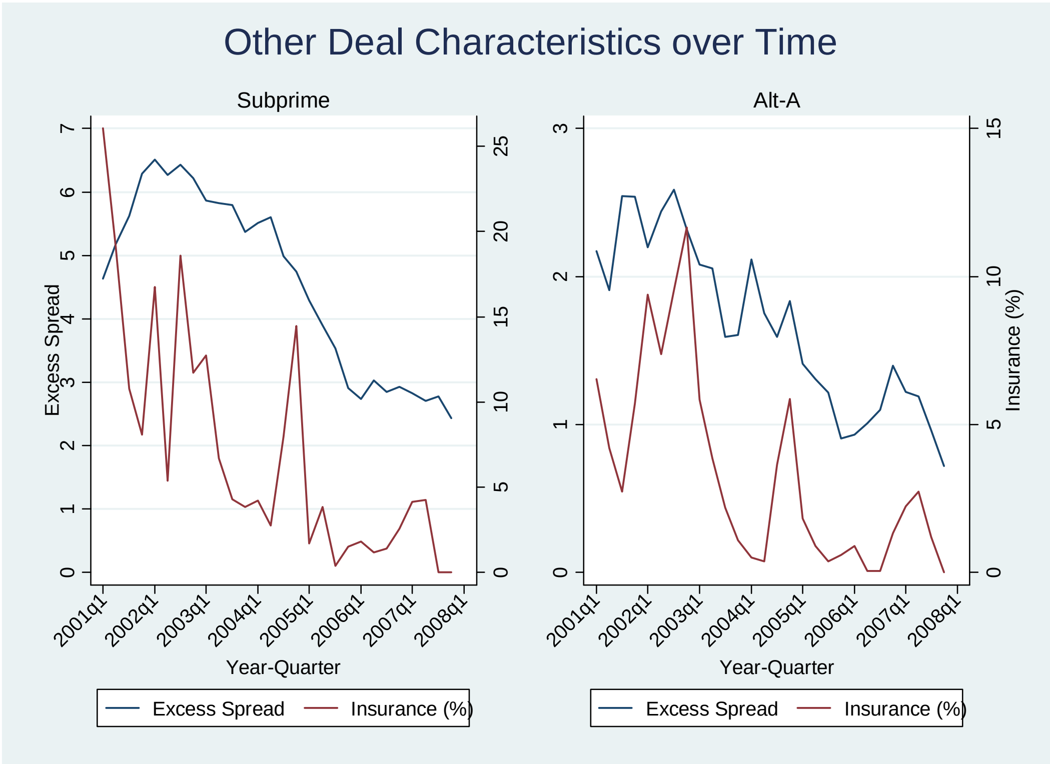


Figure 8: Observed and predicted 90+ day delinquency at 12 months

Figure plots average projected default rate by year-quarter vintage from the baseline logistic regression model ("Van Hemert model") as well as two alternative more complex specifications. Figure also shows the realized ex-post default rate for deals from that vintage.

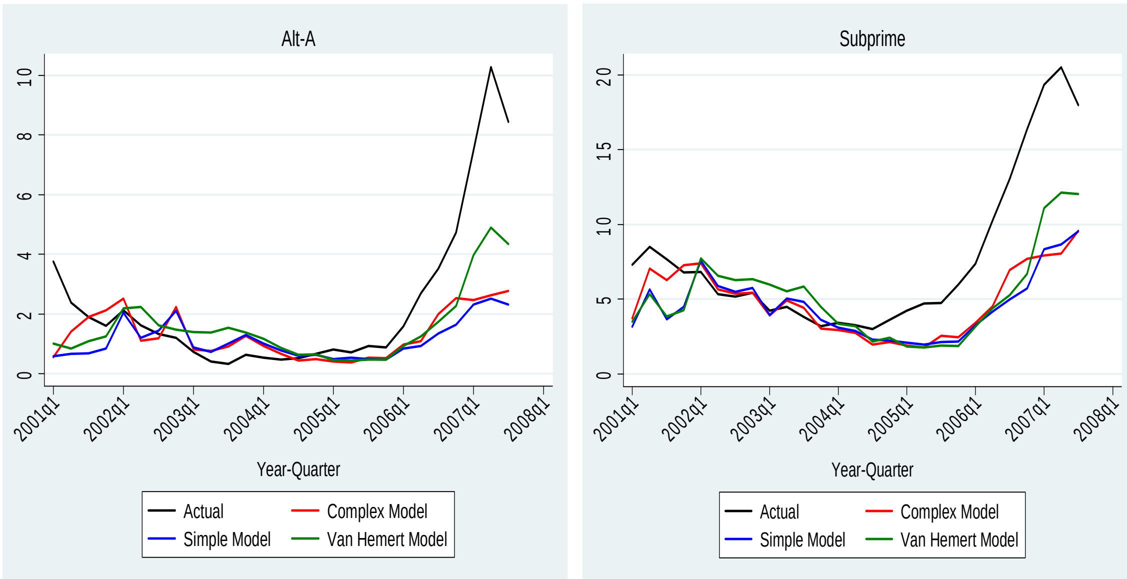
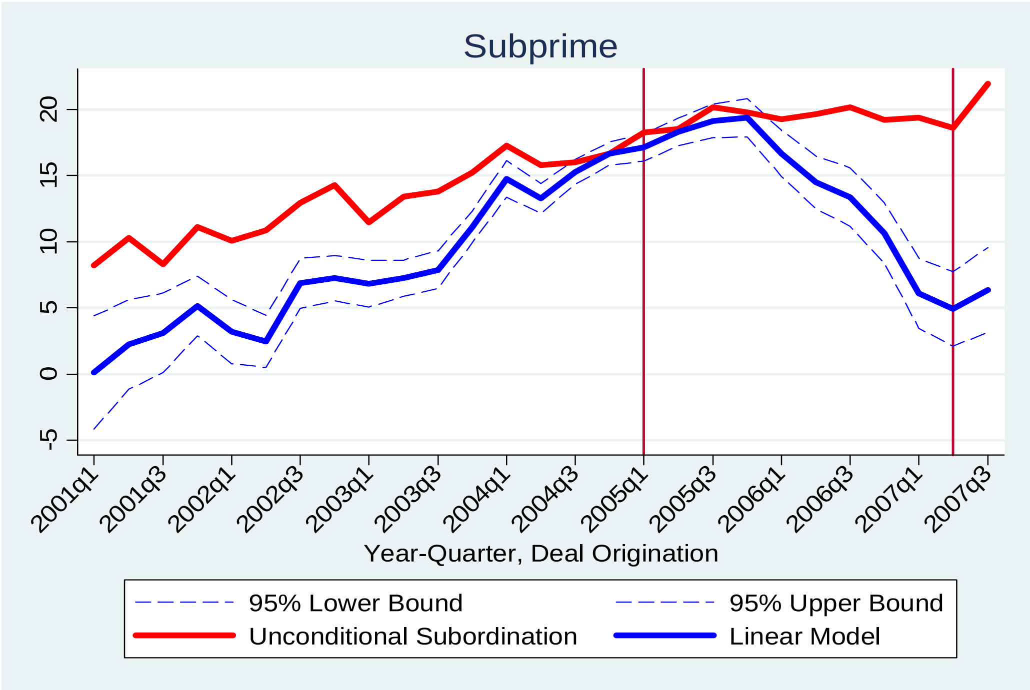


Figure 9: Predicted versus actual subordination

A. Subprime deals



B. Alt-A deals

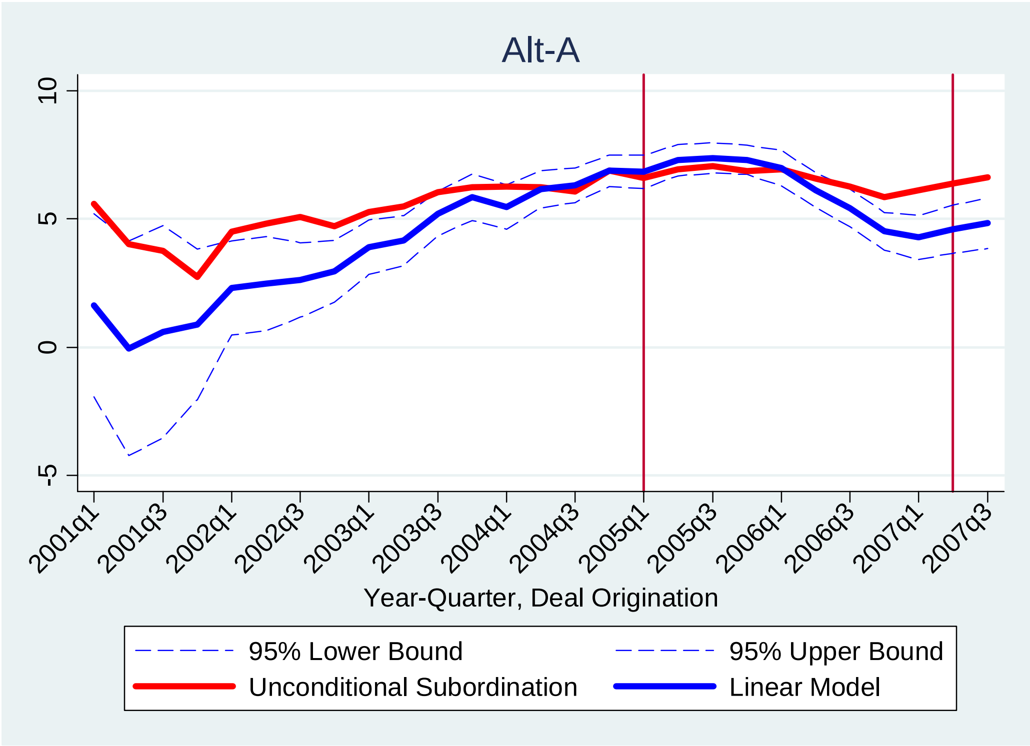


Table 1. Deal characteristics

Table provides summary statistics for our sample of 3,001 subprime and Alt-A deals issued between 2001 and 2007. Data is drawn from ABSNet, Bloomberg and LoanPerformance.

	Subprime	**Alt-A**	**All**
Number of deals	1539	1462	3001
Total number of securities	25463	32532	57995
Securities per deal, median	17	19	18
AAA securities per deal, median	5	10	6
Credit enhancement			
Percent of deals with bond insurance	13	8	11
Average value of insurance (%FV)	5	1	3
Excess spread at origination (%), median	3.7	1.1	2.6
Excess spread at origination (%), average	4.1	1.4	2.8
Deal size ($m):			
Mean	901	590	750
25^{th} percentile	527	320	398
50^{th} percentile	799	487	633
75^{th} percentile	1130	748	960
Fraction of AAA (%)			
Mean	82	94	88
25^{th} percentile	79	93	81
50^{th} percentile	82	94	90
75^{th} percentile	84	95	94
Fraction of non-AAA securities (mean, %)			
AA rating	8	3	6
A rating	5	1	3
BBB rating	4	1	2
BB rating	1	0	1
Unrated or OC	1	2	2
CRAs that rated the deal (%)			
Rated by all three CRAs	48	14	31
Rated by S&P and Fitch	3	18	10
Rated by Moodys and S&P	47	60	53
Rated by Moodys and Fitch	2	8	5
Rated by one CRA only	1	0	1

Table 2. Mortgage characteristics

Table presents summary statistics for mortgages underlying the 3001 deals summarized in Table 1. Data is drawn from LoanPerformance.

	Subprime	Alt-A	All
Loan amounts			
Number of loans, total	8,535,002	3,177,044	11,700,000
Number of loans per deal, average	5,553	2,170	3,903
Loan size (average)	257,277	431,068	323,717
Combined loan-to-valuation ratio (%)			
Average (%, value-weighted)	82	75	79
10th percentile	68	58	63
50th percentile	80	80	80
90th percentile	95	85	95
% missing	0	0	0
Junior-lien mortgages (% of deal size, avg)	7	0	4
FICO scores			
Average (value-weighted)	625	707	656
10th percentile	546	647	563
50th percentile	626	709	660
90th percentile	708	777	754
% Missing	0	1	0
Debt-to-income ratio			
Average (value-weighted)	41	37	40
10th percentile	28	25	27
50th percentile	43	39	42
90th percentile	50	48	50
% Missing	28	57	39
Interest only loans			
% IO mortgages	18	53	31
Number of deals with IO > 1%	1,115	1,156	2,271
Number of deals with IO > 75%	33	453	486
Documentation (%):			
Full	59	28	47
Low	40	65	50
No	0	6	2
Missing	0	1	0

Table 3. Time series patterns for key variables

Panel A. Subprime deals

	2001	2002	2003	2004	2005	2006	2007	All
Deal characteristics								
Number of deals	39	80	159	280	365	419	197	1,539
Deal size, average ($m)	473	617	769	979	1,010	911	871	901
Fraction of AAA securities (%)								
Average	90	88	86	84	81	80	81	82
Median	89	85	85	83	81	80	80	82
Excess spread (median, %)	6.1	6.3	5.8	5.1	3.5	2.8	2.8	3.7
Fraction deals with bond insurance	46	33	19	20	8	6	12	13
Percent deals rated by all three CRAs	49	51	64	57	53	39	28	48
Loan characteristics, value weighted								
CLTV (%, average)	83	82	83	84	86	87	87	82
Junior-lien mortgages (average % of deal)	14	9	5	3	5	10	11	7
FICO, average	595	613	620	622	628	628	631	625
Debt-to-income (%), average	23	25	26	29	30	32	32	41
Interest-only mortgages (avg % of deal)	0	0	2	11	27	21	16	18
Low/no-doc mortgages (% of deal, avg)	23	30	34	37	42	46	45	41
12-month-ended HPA (OFHEO)	9	8	9	16	18	12	3	12

Panel B. Alt-A deals

	2001	2002	2003	2004	2005	2006	2007	All
Deal characteristics								
Number of deals	11	66	150	262	370	352	251	1,462
Deal size, average ($m)	423	374	403	529	618	689	653	590
Fraction of AAA securities (%)								
Average	96	95	94	94	93	94	94	94
Median	96	95	95	94	94	94	94	94
Excess spread (median, %)	2.3	2.0	1.5	1.3	1.0	1.0	1.0	1.1
Fraction deals with bond insurance	73	9	10	8	8	4	8	8
Percent deals rated by all three CRAs	18	6	4	4	6	25	28	14
Loan characteristics, value weighted								
CLTV (%, average)	77	79	75	80	80	82	82	75
Junior-lien mortgages (average % of deal)	0.0	0.0	0.0	0.2	0.1	0.1	0.6	0.2
FICO, average	692	702	708	706	706	706	708	707
Debt-to-income (%), average	16	11	10	16	15	17	19	37
Interest-only mortgages (avg % of deal)	1	1	11	44	58	64	63	53
Low/no-doc mortgages (% of deal, avg)	67	59	65	63	66	77	80	71
12-month-ended HPA (OFHEO)	11	9	9	17	18	13	2	12

Table 4. Loan-level default model

Table shows regression coefficients from baseline loan-level default model. Logistic regression, based on a 10% LoanPerformance sample using data up to Q4:2007. [In paper, this specification is estimated recursively using different historical samples corresponding to data available at various points in time]. Reported regression coefficients are normalized to reflect marginal effects at the mean of the data.

Dependent variable: =1 if mortgage is in default (defined as +90 delinquent, prepaid with loss or REO) 12 months after origination. =0 otherwise.

Underwriting variables	
LTV	0.000942***
	(0.000157)
FICO	-0.000340***
	(2.30e-05)
12-month trailing HPA	-0.172***
	(0.0104)
Balloon loan	0.00432***
	(0.00140)
Low Doc	0.0171***
	(0.00131)
No Doc	0.0234***
	(0.00134)
Investor	0.0131***
	(0.00151)
DTI	0.000318***
	(3.33e-05)
DTI Missing	0.00874***
	(0.00218)
Cashout Refinance	-0.0117***
	(0.00309)
ln(loan amount)	0.0163***
	(0.000843)
Prepayment Penalty	0.0116***
	(0.000558)
Other covariates	
Year dummies	yes
Local unemployment rate	yes
Spread at Origination	yes
N	1266127
Pseudo R-Squared	0.1489

Table 5. Determinants of AAA subordination

Deal-level regression of the determinants of AAA subordination. Linear regression, based on deal-level data summarized in Table 1 and Table 3. Standard errors clustered by year x quarter. "Projected default rate" refers to the projected 12 month default rate based on the benchmark logistic default model, estimated using historical data prior to the six month period in which the deal was issued.

Dependent variable: Subordination below AAA class (percentage points).

	Subprime		**Alt-A**	
Credit risk				
Projected default rate	0.994***	1.052***	0.911***	1.024***
	(0.247)	(0.269)	(0.231)	(0.205)
Projected default rate^2	-0.0120	0.0105	-0.182*	-0.236***
	(0.0815)	(0.0778)	(0.0926)	(0.0792)
F-test: Projected default variables [p-value]	0.0000***	0.0000***	0.0000***	0.0000***
Other deal characteristics				
Bond insurance (1=yes)	-0.523***	-0.533***	0.0294	0.0434
	(0.108)	(0.108)	(0.0529)	(0.0471)
Fraction of deal with bond insurance	-0.00911**	-0.00885**	-0.00601	-0.00646
	(0.00434)	(0.00423)	(0.00450)	(0.00400)
Weighted average coupon rate	-0.00927	0.0362	-0.0535***	-0.00107
	(0.0595)	(0.0615)	(0.0156)	(0.0134)
Weighted mortgage interest rate	0.0268	0.0106	0.0815*	0.00394
	(0.0252)	(0.0266)	(0.0438)	(0.0413)
Geographic concentration of loans	1.742***	1.087***	0.461***	0.284***
	(0.183)	(0.247)	(0.113)	(0.0897)
Year x quarter dummies	Yes	Yes	Yes	Yes
F-test: ratings decline over 2005-07? (p-value)[a]	0.0071***	0.0238**	0.0000***	0.116
Include aggregated loan-level controls	No	Yes	No	Yes
F-Test (p-value)		0.0000***		0.0000***
N	1539	1539	1462	1462
R^2	0.524	0.537	0.250	0.380

[a] P-value for statistical test of null that average value of year-quarter dummy during the "credit boom" period (2005:01 to 2007:Q2) to its value in 2004:Q4

Table 6: Credit ratings and ex-post default

Deal-level regression of ex-post deal-level mortgage default rate on credit ratings, projected default rate from loan level model and other deal controls. Linear regression; standard errors clustered by year x quarter. Dependent variable is weighted fraction of mortgages in the deal that are +90 days delinquent, prepaid with loss or REO 12 months after deal is issued. "Other deal controls" are the same as in Table 4: two bond insurance variables, average bond coupon rate and mortgage interest rate, and measure of geographic diversification of pool. "Projected default rate" is based on the benchmark logistic default model. Reported R^2 is based on variation in the data within year-quarters. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels.

A. Subprime

Dependent variable: Fraction of deal in default 12 months after deal is issued

	baseline	rating only	model only	model & rating	model, rating and loan covariates
Deal subordination below AAA		0.355***		0.161***	0.139***
		(0.0411)		(0.0273)	(0.0207)
Projected default rate			1.142***	0.988***	1.191***
			(0.0536)	(0.0515)	(0.0591)
Other deal characteristics	Yes	Yes	Yes	Yes	Yes
Year x quarter dummies	Yes	Yes	Yes	Yes	Yes
Loan covariates aggregated to deal level	No	No	No	No	Yes
F-test: Aggregated loan covariates [p-val]					0.0000***
N	1539	1539	1539	1539	1539
R^2	0.101	0.304	0.531	0.565	0.652

B. Alt-A

Dependent variable: Fraction of deal in default 12 months after deal is issued

	baseline	rating only	model only	model & rating	model, rating and deal covariates
Deal subordination below AAA		0.424***		0.265***	0.0382
		(0.0669)		(0.0488)	(0.0452)
Projected default rate			1.530***	1.407***	1.685***
			(0.110)	(0.0953)	(0.0609)
Other deal characteristics	Yes	Yes	Yes	Yes	Yes
Year x quarter dummies	Yes	Yes	Yes	Yes	Yes
Aggregated mortgage characteristics	No	No	No	No	Yes
F-test: Deal-level covariates [p-value]					0.0000***
N	1462	1462	1462	1462	1462
R^2	0.391	0.462	0.616	0.642	0.762

Table 7: Credit ratings and ex-post default: results for all covariates

Table displays full set of coefficient estimates for deal-level regression of ex-post deal-level mortgage default rate on credit ratings, projected default rate from loan level model and other deal controls. Linear regression; standard errors clustered by year x quarter. Dependent variable is weighted fraction of mortgages in the deal that are +90 days delinquent, prepaid with loss or REO 12 months after deal is issued. R2 is based on variation in the data within year-quarters. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels.

Dependent variable: Fraction of deal in default 12 months after deal is issued

Panel A: Subprime deals

Include covariates	No	Yes	Yes	Yes
Credit boom interactions	No	No	No	Yes
Deal subordination	0.161***		0.139***	0.132***
	(0.0273)		(0.0205)	(0.0214)
Projected delinquency rate	0.988***		1.185***	0.972***
	(0.0515)		(0.0607)	(0.0521)
Other deal characteristics				
Bond insurance (1=yes)	0.0284	0.0747	0.0228	0.0235
	(0.0450)	(0.0472)	(0.0341)	(0.0332)
Fraction of deal with bond insurance	0.00194*	0.00164	0.00131	0.00138*
	(0.000967)	(0.00105)	(0.000780)	(0.000673)
Weighted average coupon rate	0.00971	-0.103***	0.0590*	0.00385
	(0.0309)	(0.0364)	(0.0317)	(0.0266)
Weighted mortgage interest rate	-0.0637***	-0.0805***	-0.152***	-0.146***
	(0.0122)	(0.0165)	(0.0190)	(0.0206)
Geographic concentration of loans	0.737***	-0.211	-0.0602	-0.0951
	(0.199)	(0.242)	(0.194)	(0.187)
Rating strategy (omitted category = three ratings)				
Moodys & S&P		-0.0475	-0.0291	-0.0211
		(0.0462)	(0.0390)	(0.0460)
Moodys & Fitch		-0.0473**	-0.000342	0.0231
		(0.0176)	(0.0144)	(0.0249)
S&P and Fitch		-0.0618	-0.0299	0.0235
		(0.0713)	(0.0469)	(0.0486)
One rating		0.579***	0.205***	0.234**
		(0.129)	(0.0657)	(0.107)
F-test: rating strategy variables [p-value]		0.0016***	0.0242**	0.124
Aggregated loan-level covariates				
LTV		0.00231	0.0149***	0.0130***
		(0.00308)	(0.00149)	(0.00144)
FICO		-0.00134	0.000796*	0.000814*
		(0.000903)	(0.000409)	(0.000441)
HPA		-2.033**	3.411***	3.586***
		(0.760)	(0.878)	(0.908)
IO		-0.202**	-0.0701	-0.234***
		(0.0735)	(0.0578)	(0.0803)
Low doc		0.755***	0.551***	0.232**
		(0.103)	(0.0627)	(0.0890)
Investor		0.827**	0.490**	1.783***
		(0.300)	(0.184)	(0.494)
Loan level covariate interactions				
Projected delinquency rate * boom				0.404***
				(0.0698)
IO * boom				0.279***
				(0.0937)
Low doc * boom				0.475***
				(0.117)
Investor * boom				-1.622***
				(0.499)
Not Three Ratings * boom				0.0373
				(0.0276)
Year x quarter dummies	yes	yes	yes	yes
N	1539	1539	1539	1539
R^2	0.853	0.803	0.883	0.889

Table 7 (cont…)

Panel B: Alt-A deals

Include covariates	No	Yes	Yes	Yes
Credit boom interactions	No	No	No	Yes
Deal subordination	0.265***		0.0332	0.0365
	(0.0488)		(0.0463)	(0.0400)
Projected delinquency rate	1.407***		1.664***	1.580***
	(0.0953)		(0.0609)	(0.0772)
Other deal characteristics				
Bond insurance (1=yes)	0.0210	0.140***	0.0212	0.0273
	(0.0527)	(0.0448)	(0.0428)	(0.0410)
Fraction of deal with bond insurance	-0.00112	-0.00549*	-0.00247	-0.00225
	(0.00283)	(0.00303)	(0.00214)	(0.00194)
Weighted average coupon rate	-0.0652***	-0.0495***	-0.00361	-0.00967
	(0.00839)	(0.0137)	(0.00886)	(0.0103)
Weighted mortgage interest rate	0.117**	0.466***	0.0322	0.0120
	(0.0447)	(0.0440)	(0.0347)	(0.0392)
Geographic concentration of loans	-0.0348	0.164*	-0.340***	-0.348***
	(0.103)	(0.0811)	(0.0957)	(0.0871)
Rating strategy (omitted category = three ratings)				
Moodys & S&P		0.0446	-0.00456	-0.0673**
		(0.0320)	(0.0265)	(0.0320)
Moodys & Fitch		0.139***	0.0411	-0.00870
		(0.0351)	(0.0274)	(0.0323)
S&P and Fitch		0.0419	0.0157	-0.0411
		(0.0467)	(0.0363)	(0.0409)
One rating		0.354***	0.363***	0.297***
		(0.0662)	(0.0591)	(0.0602)
F-test: rating strategy variables [p-value]		0.0002***	0***	0***
Aggregated loan-level covariates				
LTV		0.0209***	0.0195***	0.0186***
		(0.00419)	(0.00175)	(0.00192)
FICO		-0.000605**	0.00177***	0.00178***
		(0.000283)	(0.000288)	(0.000275)
HPA		-1.133*	3.718***	3.748***
		(0.650)	(0.548)	(0.619)
IO		0.288***	0.145**	-0.0462
		(0.0616)	(0.0559)	(0.0980)
Low doc		0.480***	0.230***	0.213***
		(0.102)	(0.0755)	(0.0580)
Investor		0.113	0.172**	0.0310
		(0.107)	(0.0734)	(0.0856)
Loan level covariate interactions				
Projected delinquency rate * boom				0.183
				(0.153)
IO * boom				0.255**
				(0.115)
Low doc * boom				0.0473
				(0.129)
Investor * boom				0.237
				(0.139)
Not Three Ratings * boom				-0.0555
				(0.0416)
Year x quarter dummies	yes	yes	yes	yes
N	1462	1462	1462	1462
R^2	0.853	0.841	0.903	0.906

Table 8: Predictors of rating downgrades

Deal-level regression of ex-post rating downgrades on initial credit ratings, projected default rate from loan level model and other deal controls. Linear regression; standard errors clustered by year x quarter. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels.

Dependent variable: Weighted average downgrade notches

	Subprime		Alt-A	
Dependent variable: Rating downgrades				
Deal subordination below AAA	-1.043***	-0.981***	0.714*	0.410
	(0.285)	(0.296)	(0.354)	(0.357)
Projected default rate	1.946***	1.823***	2.279***	3.705***
	(0.408)	(0.487)	(0.695)	(0.973)
Other deal characteristics				
Bond insurance (1=yes)	-0.677***	-0.434**	-0.945**	-0.852**
	(0.237)	(0.163)	(0.383)	(0.359)
Fraction of deal with bond insurance	0.0136**	0.00822	0.0343**	0.0325**
	(0.00612)	(0.00666)	(0.0140)	(0.0126)
Weighted average coupon rate	-0.291	-0.241	0.356**	0.404***
	(0.346)	(0.281)	(0.157)	(0.136)
Wtd avg mortgage interest rate	1.391***	1.015***	-0.467*	-0.582*
	(0.348)	(0.345)	(0.237)	(0.292)
Geographic concentration of loans	8.611***	6.238***	0.139	-0.627
	(2.412)	(2.015)	(0.814)	(0.977)
Rating strategy (omitted category = three ratings)				
Moodys & S&P		0.418		-0.186
		(0.355)		(0.220)
Moodys & Fitch		-0.348**		-0.853***
		(0.145)		(0.286)
S&P and Fitch		0.188		0.924**
		(0.675)		(0.431)
One rating		7.161*		-1.506***
		(3.722)		(0.408)
F-test: rating strategy variables [p-value]		0.0526*		0***
Aggregated loan-level covariates				
LTV		0.0490**		0.0306
		(0.0232)		(0.0184)
FICO		0.00336		0.00513**
		(0.00267)		(0.00189)
HPA		-9.963		15.34**
		(6.688)		(5.989)
IO		0.188		0.550
		(0.563)		(0.485)
Low doc		4.490***		1.549**
		(1.352)		(0.589)
Investor		3.968**		-0.567
		(1.577)		(0.729)
Year x quarter dummies	yes	yes	yes	yes
N	1539	1539	1462	1462
R^2	0.618	0.661	0.678	0.694

Table 9. Alternative measures of ex-post performance

Regressions of realized losses and mortgage defaults on on credit ratings, projected default rate from loan level model and other deal controls. Linear regression; standard errors clustered by year x quarter. ***, ** and * represent significance at the 1%, 5% and 10% levels.

A. Dependent variable: Realized losses to date

	Subprime				Alt-A			
	rating only	model only	model & rating	model, rating and deal covariates	rating only	model only	model & rating	model, rating and deal covariates
Deal subordination below AAA	0.129***		0.0855**	0.0771***	0.540***		0.448***	0.103
	(0.0301)		(0.0349)	(0.0258)	(0.0899)		(0.0905)	(0.0734)
Projected default rate		0.304***	0.222***	0.625***		1.018***	0.810***	0.962***
		(0.0587)	(0.0722)	(0.0846)		(0.123)	(0.113)	(0.0728)
Other deal characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal-level mortgage characteristics	No	No	No	Yes	No	No	No	Yes
F-test: Deal-level covariates [p-value]				0***				0***
N	1539	1539	1539	1539	1462	1462	1462	1462
R^2	0.343	0.344	0.349	0.483	0.367	0.353	0.421	0.647

B. Dependent variable: 24 month 90+ delinquency rate

	Subprime				Alt-A			
	rating only	model only	model & rating	model, rating and deal covariates	rating only	model only	model & rating	model, rating and deal covariates
Deal subordination below AAA	0.283***		0.131***	0.113***	0.477***		0.388***	0.133***
	(0.0415)		(0.0311)	(0.0216)	(0.0782)		(0.0661)	(0.0437)
Projected default rate		1.049***	0.939***	1.198***		1.334***	1.159***	1.471***
		(0.0614)	(0.0630)	(0.0620)		(0.00223)	(0.109)	(0.0843)
Other deal characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal-level mortgage characteristics	No	No	No	Yes	No	No	No	Yes
F-test: Deal-level covariates [p-value]				0***				0***
N	1233	1233	1233	1233	1122	1122	1122	1122
R^2	0.239	0.445	0.468	0.578	0.492	0.529	0.599	0.760

C. Dependent variable: 90+ delinquency rate to date

	Subprime				Alt-A			
	rating only	model only	model & rating	model, rating and deal covariates	rating only	model only	model & rating	model, rating and deal covariates
Deal subordination below AAA	0.176***		0.0801**	0.0636**	0.512***		0.412***	0.0927**
	(0.0304)		(0.0301)	(0.0252)	(0.0644)		(0.0598)	(0.0419)
Projected default rate		0.567***	0.490***	0.834***		1.081***	0.890***	0.973***
		(0.0624)	(0.0736)	(0.0802)		(0.111)	(0.0960)	(0.0683)
Other deal characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal-level mortgage characteristics	No	No	No	Yes	No	No	No	Yes
F-test: Deal-level covariates [p-value]				0***				0***
N	1539	1539	1539	1539	1462	1462	1462	1462
R^2	0.082	0.154	0.165	0.317	0.381	0.391	0.467	0.748

Table 10: Ex-post default, year by year

Year by year estimation of specification from Table 6. (Deal-level linear regression of ex-post deal-level mortgage default rate on credit ratings, projected default rate from loan level model and other deal controls.) To conserve space, other coefficients omitted from table. Standard errors clustered by year x quarter. Dependent variable is weighted fraction of mortgages in deal that are +90 days delinquent, prepaid with loss or REO 12 months after deal is issued. "Other deal controls" same as Table 4: two bond insurance variables, average coupon rate and mortgage interest rate, and measure of geographic diversification of pool. "Projected default rate" is based on the benchmark logistic default model. ***, ** and * represent significance at the 1%, 5% and 10% levels.

Dependent variable: Fraction of deal in default 12 months after deal is issued

	Vintage							All
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**Years**
A. Subprime deals								
Baseline (just deal controls; same as Column 1 of Table 6)								
R^2	0.558	0.479	0.311	0.196	0.026	0.389	0.270	0.101
Baseline & rating								
Subordination below AAA	0.367	0.0764	0.115	0.259***	0.377**	0.497**	0.503***	0.355***
	(0.163)	(0.0552)	(0.0938)	(0.0317)	(0.0821)	(0.0975)	(0.0357)	(0.0407)
R^2	0.726	0.487	0.344	0.379	0.143	0.490	0.568	0.304
Baseline & model prediction								
Projected delinquency rate	1.133***	1.032***	0.738***	0.880***	1.543***	1.112***	1.196***	1.142***
	(0.108)	(0.0898)	(0.0959)	(0.108)	(0.0557)	(0.120)	(0.0411)	(0.0531)
R^2	0.925	0.817	0.518	0.412	0.485	0.634	0.692	0.531
Baseline & rating & model prediction								
Subordination below AAA	0.0236	-0.00973	0.0720	0.188***	0.134**	0.261*	0.215**	0.161***
	(0.0997)	(0.0277)	(0.0860)	(0.0201)	(0.0266)	(0.0974)	(0.0414)	(0.0271)
Projected delinquency rate	1.101***	1.036***	0.709***	0.691***	1.447***	0.983***	0.930***	0.988***
	(0.139)	(0.0926)	(0.108)	(0.0829)	(0.0429)	(0.165)	(0.0628)	(0.0511)
R^2	0.925	0.817	0.531	0.498	0.498	0.659	0.725	0.565
N	39	80	159	280	365	419	197	1539
B. Alt-A deals								
Baseline (just deal controls; same as Column 1 of Table 6)								
R^2	0.981	0.782	0.600	0.465	0.410	0.503	0.371	0.391
Baseline & rating								
Subordination below AAA	0.684	-0.106	0.0197	0.172**	0.558***	0.855***	0.804	0.424***
	(0.525)	(0.142)	(0.0656)	(0.0539)	(0.0699)	(0.106)	(0.417)	(0.0663)
R^2	0.990	0.786	0.600	0.499	0.628	0.581	0.439	0.462
Baseline & model prediction								
Projected delinquency rate	1.156**	1.291***	1.162***	0.889**	1.554*	1.522***	2.147***	1.530***
	(0.254)	(0.0662)	(0.0699)	(0.176)	(0.489)	(0.119)	(0.122)	(0.106)
R^2	0.999	0.874	0.773	0.616	0.564	0.642	0.688	0.616
Baseline & rating & model prediction								
Subordination below AAA	0.284***	-0.0659	0.0196	0.128*	0.448**	0.589***	-0.249	0.265***
	(0)	(0.106)	(0.0502)	(0.0417)	(0.0831)	(0.0716)	(0.324)	(0.0483)
Projected delinquency rate	0.989***	1.276***	1.162***	0.849***	1.021*	1.309***	2.320***	1.407***
	(0)	(0.0923)	(0.0707)	(0.141)	(0.373)	(0.0771)	(0.155)	(0.0944)
R^2	1.000	0.876	0.773	0.634	0.686	0.676	0.692	0.642
N	11	66	150	262	370	352	251	1462