MBS ratings and the mortgage credit boom

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Abstract

We study 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. Ratings are found to be correlated with ex-ante credit risk, and with subsequent deal performance, suggesting they contain useful information for investors. However, controlling for risk, we also find evidence of significant time-variation in credit ratings, with ratings becoming progressively less conservative around the MBS market peak between 2005-07. Deals with higher-risk mortgages, measured by a simple model, perform poorly relative to their rating over the entire sample, whether performance is measured as mortgage default rates, losses or rating downgrades. MBS deals with opaque characteristics, such as a high fraction of low-documentation mortgages, also underperform their rating, consistent with the predictions of recent theoretical literature.

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Mistakes by credit rating agencies (CRAs) are often cited as one of the causes of the current financial crisis, which began with a surge in subprime mortgage defaults in 2007 and 2008. Prior to the crisis, 80-95% of a typical subprime or Alt-A mortgage-backed-securities (MBS) deal was assigned the highest possible triple-A rating, making these securities attractive to a wide range of domestic and foreign investors. Reflecting recent mortgage defaults, however, many MBS originally rated investment-grade now trade significantly below par, and have also experienced large rating downgrades. Figure 1 plots net rating changes on subprime and Alt-A MBS issued since 2001. While net rating changes are close to zero for bonds issued early in this period, securities issued since 2005 have experienced historically large downgrades since issuance, by an average of 3-10 rating notches depending on the vintage (on a 22-notch scale).

[INSERT FIGURE 1 HERE]

Critics interpret these facts as evidence of important flaws in the credit rating process, either due to incentive problems associated with the "issuer-pays" rating model, or simply insufficient diligence or competence (e.g. White, 2009; Fons, 2008; Coval, Jurek and Stafford, 2009).[1] In their defense however, rating agencies argue that the poor recent performance of MBS ratings primarily reflects a series of large, unexpected shocks, including unprecedented declines in home prices and a sharp contraction in mortgage credit supply. The scale of these events, while not predicted by rating agencies, was also not anticipated by most other market participants. CRAs also point to repeated warnings made by them before the crisis about increasing levels of risk in non-prime MBS deals, and argue that their credit ratings became accordingly more conservative to reflect this greater risk.[2]

[1] For example, 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).

[2] In Senate testimony, Michael Kanef, Structured Finance Group Managing Director of Moody's, states: *"In response to the increase in the riskiness of loans made during the last few years and the changing*

In light of this debate, the goal of this paper is to analyze the quality of initial credit ratings assigned to subprime and Alt-A MBS deals in the period leading up to the financial crisis (2001-07). We evaluate ratings with respect to three main benchmarks. First, we test whether ratings are informative, in the sense of being correlated cross-sectionally with the level of credit risk in the MBS deal, measured either ex-ante by the quality of the underlying mortgages, or ex-post by the realized level of defaults or investor losses. Second, we test whether MBS ratings are stable, meaning that the level of ratings does not fluctuate through time after controlling for risk. Third, we test whether ratings are informationally efficient, in the sense of being a sufficient statistic for the level of credit risk in the deal. Under this hypothesis, data that is publicly available when the deal was rated and issued should not systematically predict future performance, after controlling for the rating. This is because the rating itself should reflect that information, to the extent it is relevant for credit risk.

Where applicable, we compare our results to recent theoretical literature on credit ratings, including papers by Bolton, Freixas and Shapiro (2008), Mathis, McAndrews and Rochet (2009), Skreta and Veldkamp (2009), Sangiorgi**,** Sokobin and Spatt (2008), Mariano (2008), and Faure-Grimaud, Peyrache and Quesada (2007). This research analyzes informational frictions about the misreporting or selective disclosure of the rating agency's private information about a security's quality, as well as the role of reputation. Our analysis provides empirical tests of predictions from

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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, 2007). Kanef cites aggressive underwriting standards, a decline in national home prices, and a worsening of mortgage credit conditions as the main causes for the poor performance of recent subprime vintages (p.14), and states that "*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*." (p.17). Devan Sharma, President of Standard and Poors (S&P), also highlights the extreme nature of the events that occurred, writing: *"Why did these ratings on mortgage-backed securities perform poorly? Put simply, our assumptions about the housing and mortgage markets in the second half of this decade did not account for the extraordinarily steep declines we have now seen. Although we did assume, based on historical data stretching back to the Great Depression, that these markets would decline to some degree, we and virtually every other market participant and observer did not expect the unprecedented events that occurred.* (Sharma, 2009).

this literature about the relationship between ratings bias and asset opacity, and time-series variation in ratings. (See below for further discussion.)

Our primary unit of observation is an MBS *deal*, which is a set of structured fixed-income securities linked to a common pool or pools of securitized residential mortgages. Securities in a deal are prioritized, with senior bonds having significantly less credit risk, since they have a higher claim on payments of mortgage principal, while losses are first applied against the most junior claims. Credit ratings for a structured finance deal are generally quoted in terms of the "subordination level" or "attachment point" of a particular rating class, which is the fraction of the deal that is junior to that class. For example, if a deal consists of $1bn of underlying mortgages, and $900m of AAA rated securities, then the subordination level below AAA is 10%, which means that the deal could suffer a 10% loss rate amongst the underlying loans without resulting in a loss of principal for the AAA investors, at least under a simple senior-subordinated structure. (See Section 1 for a more complete discussion).

Our empirical analysis is based on a sample of 3,144 subprime and Alt-A MBS deals issued between 2001 and 2007, comprising 59,955 individual securities. Our information on each deal includes security-level data drawn from Bloomberg and ABSNet, matched with loan-level underwriting and performance data from LoanPerformance on the mortgages underlying the deal (around 12.1 million loans in total).

First, we estimate a benchmark summary statistic for the level of credit risk in each deal, which is used later in our analysis of ratings. We split our sample into subsamples based on the date of issuance of the deal (e.g. first half 2001, second half 2001 and so on). For each six month period, we estimate a logit model of mortgage default using only data that was publicly available at the start of the period. We then substitute mortgage characteristics for the deals issued in the period into this model, and aggregate to the deal level. This produces a summary statistic for the level of credit risk in each deal, based only on ex-ante data known to rating agencies when their rating was issued. We intentionally choose a simple model structure, to minimize concerns that our methodology is influenced by subsequent knowledge about the factors that determined mortgage default during the crisis. Despite its simplicity, the logit model is actually quite informative for predicting relative deal performance, measured via default rates or investor losses.

We then turn to deal-level analysis. First, we estimate a cross-sectional regression between initial subordination levels and fundamental expected determinants of ratings: (i) credit risk as measured by our loan-level summary statistic, (ii) proxies for the correlation of defaults, in particular the geographic concentration of loans in the deal, (iii) other types of credit enhancement, including external bond insurance, and two variables that capture the level of excess spread at origination. Consistent with the informativeness hypothesis, deals with a high measured level of credit risk are rated significantly more conservatively (i.e. more subordination). Ratings are also generally related to other fundamentals in the expected directions. For example, deals with insurance or with less geographic concentration have lower subordination.

Using this same specification, we estimate how the level of credit ratings evolves over the sample period, after controlling for the level of credit risk and other fundamentals. *Unconditionally* (not adjusting for risk), average subprime subordination levels increase significantly over the first part of our sample (2001-04), and then are relatively flat between 2005-07. A similar pattern, albeit less pronounced, is evident for Alt-A deals. However, *conditional* on credit risk as measured by our summary statistic, as well as other deal characteristics, we find that ratings become progressively more generous (i.e. lower subordination) between the early 2005 and mid-2007. In other words, while risk was increasing during this period, ratings did not become correspondingly more conservative. Quantitatively, our estimates suggest that during this period, risk-adjusted AAA subordination falls by approximately 13 percentage points for subprime deals, and by 3 percentage points for Alt-A deals. Based on a decomposition exercise, we estimate about half this decline reflects the effect of lower trailing house price appreciation, while the remainder reflects changes in other mortgage underwriting characteristics and their effect on default.

This significant time-variation appears inconsistent with the rating stability hypothesis. While the magnitude of our results depends on model specification, the basic directional finding that ratings do not respond to rising credit risk between early 2005 and mid-2007 appears quite robust. Over this period, each of our main indicators of mortgage credit risk (e.g. early defaults, home price appreciation, underwriting summary statistics), suggest that risk had increased. MBS ratings do not react to these developments until after the financial crisis begins in mid 2007. We note that the decline in conditional ratings is concurrent with the peak of MBS issuance. This appears to provide some support for the prediction of Bolton et al (2009) and Mathis et al (2009) that ratings inflation is more likely to occur when securities volume, and thus the scope for current CRA profits, is high relative to reputational costs of rating errors.

The next part of our analysis studies the relationship between initial ratings and measures of realized deal performance, such as defaults and losses. Under the informational efficiency hypothesis, variation in defaults and investor losses across MBS deals should correspond well to the ordering of credit risk implied by their initial ratings. Furthermore, it should not be possible to use data available at issuance to systematically improve upon the ratings in predicting relative future performance across deals.[3]

To implement this test, we regress deal performance on our summary statistic for deal risk, other deal covariates, as well as initial ratings measured by AAA and BBB subordination and time dummies. We show that ratings are indeed correlated in the expected direction with ex-post losses and defaults, again consistent with the informativeness hypothesis. However, we also find that risky deals, measured by our model-projected default rate, perform comparatively worse than their rating would suggest. This result appears to hold over the entire sample, not just the crisis period. Furthermore, in a "horse race" type comparison, the model-projected default rate is more correlated with deal performance than the joint contribution of the two credit rating

[3] An analogy from the rational expectations literature is that it is not possible to improve upon a rational forecast using data in the ex-ante information set of the forecaster (Muth, 1961; Sargent, 1987).

variables (AAA and BBB subordination). Our summary statistic for credit risk also predicts rating downgrades, which in principle should be unforecastable if initial ratings are formed efficiently.

These findings appear inconsistent with the informational efficiency hypothesis. Moreover, our analysis allows us to identify which exactly which types of deals underperform relative to their initial ratings. We pay particular attention to deals with a high concentration of interest-only and low- and no-documentation mortgages. These loan types became increasingly popular during the credit boom; for example, amongst Alt-A deals, the fraction of interest-only loans grew from only 0.4% in 2001 to 62.3% by 2007. Limited performance history, especially during prior downturns, makes these loan types more difficult for rating agencies to evaluate. In addition, limited documentation mortgages entail much more asymmetric information, because the rating agency must rely on the borrower's report of their income, rather than verifiable information. Skreta and Veldkamp (2009) predicts that rating inflation should be greater for "opaque" securities, for which there is more residual uncertainty about fundamental security value. We view the concentration of interest-only and low-documentation mortgages in the MBS deal as reasonable proxies for opacity amongst our sample.

Empirically, we find that deals with a high fraction of low-doc and IO mortgages, or with a high fraction of investor loans, perform significantly worse (conditional on their rating) than other types of deals. Results are particularly robust for the fraction of low-documentation mortgages, and are also stronger amongst Alt-A deals, which have a higher fraction of non-standard mortgage types. This result appears consistent with the opacity prediction of Skreta and Veldkamp (2009). It is also consistent with the findings of Rajan, Seru and Vig (2009) that low-documentation deals became progressively of worse quality over this period relative to what a backward-looking statistical model would predict. Finally, we also find that subprime deals rated by a single CRA perform poorly relative to their initial credit ratings. This replicates a finding of Benmelech and Dlugosz (2009), who study collateralized debt obligations (CDOs). We note that these single-rater deals make up a small fraction of our MBS sample, however.

The evidence in this paper relates to an active current policy debate about the role of rating agencies in the crisis, and appropriate regulation of the rating industry. Congress is currently drafting new legislation to toughen oversight of rating agencies, while the SEC has announced new rules to limit selective disclosure of ratings opinions by securities issuers. Other commentators have proposed fundamental changes to the method by which ratings are solicited, such as the "platform pays" structure proposed by Mathis, McAndrews and Rochet (2009).

To assess the need for regulatory reform, it is important to have reliable evidence about past rating performance. The evidence presented in this paper shows that MBS credit ratings are informative about credit risk, and do provide useful information to help guide investors, risk managers and regulators. However, we also find evidence that highlights apparently significant shortcomings of the rating process during this period, particularly during the market peak in 2005-07, when incentives to produce generous ratings were likely to be the strongest.

The rest of this paper proceeds as follows. Section 1 provides background information about MBS securitization. (Readers familiar with these details may choose to skip this section). Section 2 presents a selective review of the credit ratings literature. Section 3 describes our main hypotheses. Section 4 describes our data and presents stylized facts. Section 5 describes the econometric model used to estimate a model-predicted default rate. Section 6 studies the determinants of ratings, and time-variation in the level of ratings. Section 7 presents evidence on the relationship between ratings and ex-post deal performance. Section 8 concludes.

1. Institutional Background

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

1.1 Overview of non-agency MBS

The non-agency market consists of MBS deals that do not carry a credit guarantee from the GSEs Fannie Mae and Freddie Mac, or the government agency Ginnie Mae. Investors in non-agency MBS are exposed to credit risk relating to fluctuations in default rates on mortgages underlying the deal. 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 claims is referred to as the equity tranche. For subprime deals, 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 vast majority of the capital structure is 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.

Reflecting this structure, in our empirical work subordination is calculated as follows:

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

For example, BBB subordination of 5% means that the top 95% of the capital structure for that deal receives a rating of BBB or higher. The 5% subordinate class of claims may include both traded securities with a rating below BBB, or an unrated equity tranche. A higher level of subordination implies that the deal is rated more conservatively, other things equal, because less of the deal obtains a given credit rating or better. Deals made up of riskier mortgages should have more subordination, because the distribution of potential credit losses is shifted to the right.

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 cumulative loss performance tests, 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.

1.2 The credit 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 through time and 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.*" (S&P, 2007, p.4). Despite these intentions, academic research has uncovered evidence of significant differences in expected loss rates for AAA securities across different instruments (e.g. Mason and Rosner, 2007, which compares 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, and thus comes closer to measuring expected loss. 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.

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.

In order to construct the baseline, the rating agency uses historical loan-level 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. 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.
To simulate the loss distribution, the rating agency needs to estimate the sensitivity of losses to local 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.

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 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. Literature review

In this section we review theoretical literature on credit ratings, as well as selected empirical evidence related to our paper. Readers are referred to these papers for links to further research.

2.1 Theoretical literature

Several recent theoretical papers study incentive problems in the credit rating process. Bolton, Freixas and Shapiro (2008) models a security issuer who obtains ratings from one or more CRAs, each with a private signal about the security's value. Each agency can report its signal truthfully, or misreport it. Exaggerating the security's value leads to an exogenous reputation cost if detected by investors, but provides a higher market share and fee income to the CRA in the current period. Bolton et al find that rating inflation will be greater when there is a larger fraction of "naïve" investors, and when the potential for current fee income is high relative to the reputation cost of misreporting. The presence of multiple CRAs also generates more rating inflation, through two channels: (i) competition amongst CRAs causes a "race to the bottom" as they bid to win market share by inflating ratings; (ii) it allows the issuer to engage in "shopping", soliciting multiple ratings but revealing only the most favorable ones.

In related work, Skreta and Veldkamp (2009) study the equilibrium relationship between asset complexity and rating inflation. Complexity is defined as the residual uncertainty in fundamental asset value conditional on the signal of the rating agency. Rating bias in equilibrium is minimized either when complexity is low and CRA reports are very similar, or when complexity is extremely high, and credit ratings are uninformative. In the intermediate region, however, rating shopping and rating inflation is generally increasing in the degree of complexity of the security being rated. Sangiorgi, Sokobin and Spatt (2009) make a similar prediction, that rating bias and selection effects are largest for securities where there is the greatest degree of heterogeneity in views across CRAs about true security value.

The role of reputation is further explored in Mathis, McAndrews and Rochet (2008), which studies an infinitely repeated game in which the rating agency at a point in time may be of two types. An honest agency must always correctly report their signal of the security's quality, while a dishonest CRA can choose to give an incorrect report. Mathis et. al. show that when the fraction of CRA revenue from rating opaque securities is large enough, the CRA of dishonest type will always lie with positive probability in equilibrium. For some parameters an equilibrium with "reputation cycles" is possible. When the CRA's reputation is poor, there is no inflation and the CRA builds reputation by truthfully reporting its signal. Over time, investor optimism increases, and at some point, the CRA starts reporting an inflated value for the security's quality. Eventually, following a negative shock, this misreporting is discovered by investors, who then become more pessimistic.

Also related, Opp and Opp (2009) present a model where rating inflation occurs in equilibrium not because investors are fooled by misreported ratings, but because ratings are built into capital requirements and other financial regulation. Other related theoretical work includes Mariano (2008), which also studies the role of reputation, Faure-Grimaud, Peyrache and Quesada (2007), and Boot, Milbourn and Schmeits (2006).

2.2 Related empirical work

A large body of empirical research studies credit ratings, nearly always focusing on ratings of corporate bonds. CRAs claim to follow a "through the cycle" approach to bond ratings, meaning that ratings reflect default risk over the life of the bond, and do not react to short-run economic conditions beyond their effect on lifetime default risk. Amato and Furfine (2004) summarizes literature on rating procyclicality, and concludes that CRAs generally react appropriately to changes in business cycle conditions. While Blume, Lim and McKinley (1998) argue that corporate bond ratings have become progressively more conservative over time, Amato and Furfine (2004) argue that this finding largely disappears after controlling appropriately for firm-level measures of risk.

Turning to structured finance ratings, most similar to our paper in terms of data, Nadauld and Sherlund (2008) study interactions between MBS primary and secondary markets, also using a matched dataset of mortgages and MBS for a sample of subprime deals. Their main result is that following the passage of SEC regulation reducing capital requirements for broker-dealers, these dealers disproportionately increase mortgage purchases in areas with high price appreciation but lower credit quality on other dimensions, suggesting a link between secondary market MBS demand and the supply of mortgage finance. These authors also present evidence on credit ratings, finding that MBS deals from areas with higher past house price growth have more generous ratings. Although the focus of our paper is different to Nadauld and Sherlund, we do consider past house price appreciation as one of the determinants of ratings, and confirm their finding that high past appreciation is associated with less conservative ratings.

Benmelech and Dlugosz (2009) study ratings on asset-backed collateralized debt obligations (CDOs). These authors document strikingly large CDO rating downgrades amongst recent vintages, consistent with the evidence presented in Figure 1. Furthermore, these authors find that securities rated by one agency are more likely to be downgraded, and are downgraded more severely, suggestive of shopping and selective disclosure of ratings by security issuers. Also studying CDOs, Griffin and Tang (2009) find that ratings deviate from risk as measured by a rating agency's quantitative internal credit model, suggesting that judgemental adjustments were applied to the model estimates. However, these adjustments do not improve performance; results from the internal model are more informative for predicting performance than the public credit rating. As described later, we find a similar result for MBS. Credit risk estimated by a simple model is more informative for predicting deal performance than the announced ratings.

A related and important empirical question is whether credit ratings actually matter for investor decisions or bond prices. Kliger and Sarig (2000) provide convincing quasi-experimental evidence that the information in corporate bond ratings affects prices, by studying the introduction by Moody's of bond rating modifiers (e.g. an A rating is split into A1, A2 or A3). They find the information revealed by this refinement of ratings affects the relative pricing of securities which previously had the same rating. In addition to their informational role, ratings may also matter simply because they are built into financial regulation and capital requirements. Kisgen and Strahan (2009) present evidence consistent with this hypothesis. In particular they show that when DBRS is approved by the SEC as a nationally registered statistical rating organization (NRSRO), prices for corporate securities *already* rated by DBRS shift based on their DBRS rating, especially around regulatory rating boundaries.

Finally, Adelino (2009) presents evidence that amongst MBS with a given rating, bond prices have predictive power for future performance. This suggests prices contain useful information on risk, implying that investor demand reacts to fundamentals as well as the rating. However, notably, this result does not obtain for triple-A rated securities, suggesting that investors in this class just "buy the rating". Together, this evidence in these three papers strongly supports the view that MBS ratings do matter for security prices and mortgage supply.

3. Empirical predictions

The main goal of our paper is to evaluate the quality of ratings for subprime and Alt-A MBS deals in the period leading up to the financial crisis, and to compare our empirical findings to relevant theoretical literature. This section describes the main hypotheses we test empirically.

As described in Section 1, we measure credit ratings by the level of subordination below different rating classes. Our empirical tests also make use of a projected mortgage default rate for each deal, based on a simple loan-level model, which is used as a summary statistic for the level of credit risk in the deal. Importantly, for each deal the model is estimated and the statistic constructed only using ex-ante data available at the time the deal was issued and rated. Details of the model are described in Section 5.

Hypothesis 1 (Rating informativeness): *Subordination is increasing in the level of credit risk in the deal, and correlated in the expected direction with other deal characteristics.*

Our first hypothesis is that subordination increasing in the level of credit risk facing investors, measured by the model-projected default rate on the mortgages underlying the deal. We also expect that subordination will be (i) increasing in the *variance* of credit losses (such as geographic concentration), which increase the probability of losses for senior investors; (ii) decreasing in the strength of other types of credit enhancement that substitute for subordination, such as excess spread at origination and the presence of external bond insurance.

Hypothesis 2 (Rating stability): *The level of ratings remains constant through time, after controlling for the level of credit risk and other forms of credit enhancement.*

We first document time-series trends in *unconditional* subordination in the Alt-A and subprime markets. We then estimate changes in *conditional* subordination, that is, residual changes in average ratings after controlling for mortgage credit risk and other forms of credit enhancement. This analysis allows us to examine claims that credit rating inflation is most prevalent during periods when issuance volume is high, and CRAs have stronger incentives to relax standards in order to increase current revenue. (This argument is modeled formally in Mathis, McAndrews and Rochet, 2008, as discussed in Section 1). In our sample, MBS issuance peaks in the period between the start of 2005 and the middle of 2007. Thus we particularly examine changes in rating standards around this period.

***Hypothesis 3 (Informational Efficiency)**: Information available at the time of the initial rating does not systematically predict variation in deal performance, after controlling for ratings.*

Our third hypothesis is that credit ratings about the MBS efficiently summarize available data about credit risk at the time the deal is issued. Under this hypothesis, the performance of MBS deals should correspond well to the ordering of credit risk implied by their initial ratings. Furthermore, data available at issuance should not be able to systematically predict deal performance, after controlling for ratings, since such information, if informative for the probability of investor defaults, should already be reflected in the rating.

We test this hypothesis by regressing deal performance on credit risk measured by the model-projected default rate, other deal covariates, initial ratings at different points in the capital structure, and a set of time dummy variables. We examine several measures of deal performance: mortgage defaults, realized investor losses or rating downgrades. We test this hypothesis by estimating whether either the model-projected default rate, and other summary information about the type of mortgages in the deal, systematically predicts relative performance after controlling for the rating.

The characteristics of deals that underperform their rating during the crisis is also of independent interest. In particular, we study the relative performance of deals with a high concentration of interest-only and low- and no-documentation mortgages. As argued in the

Introduction, these mortgage types had relatively limited performance history, and involve more uncertainty about performance during a downturn, especially in the case of low-documentation mortgages, where originators must rely on the borrower's report of their income, rather than verifiable information. Skreta and Veldkamp (2009) predicts that rating inflation should be greater for "opaque" securities, for which there is more residual uncertainty about fundamental security value. We view the concentration of interest-only and low-documentation mortgages in the MBS deal as reasonable proxies for opacity amongst our sample. This test is summarized in Hypothesis 3a below.

Hypothesis 3a (Ratings and opacity): *Deals with opaque mortgage collateral, such as a high fraction of low-documentation mortgages or interest-only mortgages, do not systematically underperform other deals relative to their respective initial credit rating.*

4. Data and stylized facts

Our empirical analysis is based on a sample of 3,144 subprime and Alt-A MBS deals issued between January 2001 and December 2007. This sample is constructed our sample by matching security-level information from Bloomberg and ABSNet and mortgage-level data from LoanPerformance, and aggregating that information to the deal level.

From Bloomberg and ABSNet we collect information on the initial characteristics of each security at the time of issuance, including its face value, coupon rate, position in the seniority structure and other features. We also record its initial and current credit rating from each of Moody's, S&P, Fitch and DBRS. From LoanPerformance we obtain information on the underwriting characteristics of each mortgage in each deal, such as the loan size, date of origination, borrower credit score, loan-to-valuation ratio, property zip-code and so on. We also make use of information from LoanPerformance on the ex-post performance of each mortgage at different horizons after the deal was issued (i.e., whether the loan is prepaid, current, delinquent, in foreclosure etc.).

We classify deals as subprime or Alt-A based on their assignment in LoanPerformance. In our empirical work we generally analyze these two subgroups separately. For comparability reasons, we drop deals backed by negative amortization mortgages (also known as option ARMs), a type of mortgage where borrowers make very low initial monthly payments, and the loan balance increases over time. Appendix A provides more information on our Bloomberg, ABSNet and LoanPerformance data, as well as a more detailed description of how our final sample is constructed.

Figure 3 plots the time-series of total securitization activity for our sample. We also plot total securitization volume in these two sectors as reported by the mortgage industry newsletter Inside Mortgage Finance. Comparing the two sets of figures, the Figure shows our data represents a high fraction of total nonprime securitization volume over this period. (Our sample covers a higher fraction of subprime volume relative to Alt-A, because we drop negative amortization deals, which are nearly always classified as Alt-A.) In total, our sample represents an underlying total flow of $2.4tr in nonprime securitized mortgages over this seven year period.

[INSERT FIGURE 3 HERE]

Figure 3 highlights the striking growth and subsequent collapse of deal flow in the nonprime MBS market. Issuance grew rapidly between 2001 and 2005. At the market peak from early 2005 to mid 2007, around 250 new deals were being issued each quarter in subprime and Alt-A combined, or around $200bn of volume. This issuance declined rapidly beginning in the second half of 2007, with no new deals being issued in 2008.

4.1 Measuring credit enhancement

For each deal, we calculate the level of subordination below different credit rating levels, also known as the “attachment point” of the rating class. As described in Section 1, we measure subordination below rating *i* as the fraction of claims on the mortgage collateral in the deal that are junior to bonds with a rating of *i* or higher. These junior claims include both traded securities with a rating lower than *i*, and the face value of the overcollateralization or equity tranche. When calculating these subordination levels we take care to avoid double counting by excluding tranches that are reported in ABSNet with a nominal face value but do not have a claim on mortgage principal, such as interest only and exchangeable tranches. See Appendix A for more details.

We also construct several variables to measure other types of credit enhancement on each deal. We first construct a measure of the *correlation* of mortgage losses. The primary source of loss correlation in MBS deals comes from common macroeconomic shocks, particularly home price appreciation and economic conditions. The less diversified the deal against these shocks, the greater the risk of losses to bond investors high in the capital structure. To measure the extent of diversification, we construct a variable that measures the sum of the squared share of mortgages in the deal originated from each US state. This variable is increasing in the geographic concentration of the deal, and is bounded between 0.02 and 1. A value of 1 means all the mortgages in the deal were originated in a single state, and thus are least diversified against idiosyncratic local housing or economic shocks.

In addition, we record whether the deal has external bond insurance, and the face value of this insurance as a fraction of the deal size. We also calculate both the average mortgage interest rate for the deal, and the average interest rate paid to bondholders. Net of servicing fees, the difference between these two reflects the excess spread of the deal at origination. As discussed in Section 1, the accumulation of excess spread over time provides additional credit protection to MBS security-holders.

4.2 Stylized facts

Summary statistics for the deals in our sample are summarized in Table 1. The average deal has face value of $749m, 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 claims issued in Alt-A deals receive the highest possible triple-A rating; 93.1% compared to 82.4% for the subprime deals. These figures match closely with average subordination rates reported from other sources (e.g. Ashcraft and Schuermann, 2008; Gorton, 2008), suggesting our approach for cleaning the security-level data works well. (This methodology is described in more detail in Appendix B).

Table 1 also presents information about the distribution of the number of CRAs that rated each deal. Nearly all deals are rated by two or three rating agencies, amongst four rating agencies that are active in this market over our sample period, Moody's, Standard and Poor's, Fitch and DBRS. Amongst this group, Moody's and S&P have dominant market shares. We note that almost no deals are rated by a single CRA, only 0.3% of subprime deals and 0.4% of Alt-A deals.

[INSERT TABLE 1 HERE]

Table 2 presents summary statistics for the mortgage collateral underlying these deals. On average, each subprime deal is backed by 5,506 individual mortgages, while each Alt-A deal is backed by 2,114 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 non-standard 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. For example, the fraction of interest-only mortgages increases from only 0.0% and 0.4% in subprime and Alt-A deals respectively in 2001, to 17.4% and 54.0% respectively by 2007. Table 3 also documents There are notably trends in other types of credit enhancement also. For example, the fraction of deals with bond insurance declines significantly over the sample period, both in subprime and Alt-A.

[INSERT TABLE 3 HERE]

4.3 Trends in credit enhancement

Trends in subordination are presented in Figure 3, and also documented graphically in Figure 4. This Figure plots time-series trends in subprime and Alt-A subordination at different points in the capital structure over the period 2000-2008, measured on a quarterly basis. The Figure also marks with dashed lines the period of peak MBS issuance, between Q1:2005 to Q2:2007.

[INSERT FIGURE 4 HERE]

The Figure highlights interesting trends in subordination over the sample. In the first part of the sample, up to the start of 2005, the rating of subprime RMBS deals did indeed become more conservative, consistent with CRA claims. A similar trend, albeit less pronounced, is evident in the Alt-A market. As shown in Table 3, this increased subordination is partially offset by declining levels of credit enhancement, namely insurance and excess spread. In the peak period between the start of 2005 and the middle of 2007, subprime ratings are close to stable, while Alt-A subordination declines somewhat. Finally, subordination increases sharply, especially in the subprime market, in the last two quarters of our sample, after the onset of the crisis.

While these trends are quite striking, they must be interpreted with caution, given that the characteristics of MBS deals and the quality of the underlying collateral evolved significantly over this seven year period. In the next part of our analysis, we construct a simple measure of credit risk, and adjust these unconditional estimates to reflect changes in collateral quality and other deal characteristics, such as geographic concentration and credit enhancement.

5. Loan-level model

As a precursor to our evaluation of MBS ratings, in this section, we present estimates of a loan level econometric model of mortgage defaults. This model is used to construct a summary statistic for the level of credit risk in each deal, based only on data available to rating agencies at the time the deal was rated. To facilitate this, we follow the following steps:

1. We split our sample of deals into six-month subsamples (first half 2001, second half 2001 etc.). We then estimate the model separately for each subsample, using only mortgage and macroeconomic data that was available at the start of the six-month period.
2. For each deal issued during the six month period, we substitute each mortgage in the deal into the econometric default model, and calculate its projected default probability.
3. We aggregate this model-projected default rate up to the deal level, weighting by the face value of each mortgage.

The default model is a simple logit regression based on a 10% LoanPerformance sample. We use all the LoanPerformance data, not just data from mortgages in our sample of MBS deals. This 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.

Explanatory variables included in the model include macroeconomic data and the key underwriting variables supplied in the LoanPerformance database. 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 past local house price appreciation, measured by the trailing percent change in the MSA-level OFHEO index. We examined a number of methodology documents from Moody's and S&P in the early part of our sample, and verify that each of these underwriting variables was amongst the deal characteristics considered by the rating agencies when estimating ratings. Thus, it is not the case that our measure of credit risk exploits data that we consider but CRAs at the time did not.

Table 4 presents estimates of the logit model over the full sample period up to 2007:Q4. 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 4 HERE]

Results in the Table are consistent with other literature estimating the determinants of default over this period, such as Demyanyk and Van Hemert (2009), Haughwout, Peach and Tracy (2008), and Bhardwaj and Sengupta (2009). Most notably, 12-month trailing home price appreciation (HPA) is significantly negatively correlated with subsequent mortgage default. (Note, unlike most other papers, this is a measure of HPA over the previous 12 months, not realized HPA after the deal is issued). The explanation for this correlation is that HPA is highly positively autocorrelated (Case and Shiller, 1987); thus, high HPA today in the recent past is also associated with high future HPA, increasing borrower equity and discouraging default.

Figure 5 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 logit 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 2006. Unsurprisingly, this suggests that it was not possible to fully predict the magnitude of defaults using a mechanical backward-looking model, unsurprising given the sharp deterioration in the US housing market and credit conditions observed leading up to the crisis.

[INSERT FIGURE 5 HERE]

Sections 6 and 7 present our evidence on credit ratings, which make use of the model-projected default rate estimated via this model. We emphasize that this logit model is not intended to be a comprehensive or "best practice" model of credit risk. To the contrary, we choose an intentionally simple model structure, and only variables that CRAs also claim to consider, minimizing concerns that our modeling decisions are influenced by our knowledge of the ex-post evolution of defaults. While ratings incorporate all the data in our model, at least in principle, our model excludes several 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. Given this more complex approach, ratings at different points in the capital structure would be expected to be a substantially better indicator of the level of credit risk in the deal than our model-projected default rate.

6. Determinants of credit ratings

The first part of our empirical work studies the determinants of 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.

Table 5 below presents baseline results for the deal level regression. Consistent with the rating informativeness hypothesis discussed in Section 3, the Table shows that the fundamental variables are indeed correlated in the expected way with the amount of required subordination on the deal. Most relevant, the model-projected default rate from the logit model is positive as expected, and highly 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, while deals with more bond insurance also have lower subordination on average.

[INSERT TABLE 5 HERE]

The regression model in Table 5 also includes year-quarter dummies. In Figure 6, 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 13 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 6]

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.

6. 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 0.092 to 0.275, however, including instead the model projected default rate causes the R^2 to rise by more than twice as much, from 0.092 to 0.483.

Columns 4 and 5 include both AAA subordination and the model-projected default rate in the specification. This provides a test of the informational efficiency hypothesis, 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. Panel A of Table 7 presents these results for subprime deals, while panel B presents results for Alt-A. 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, we find that deals with a high fraction of low-doc and IO mortgages, as well as deals with a high fraction of loans to investors, perform worse compared to their rating than other types of deals. Interest-only and low-documentation mortgages become an increasing fraction of securitized deals over our sample period; for example, the fraction of Alt-A loans in our sample that were interest only grew from 0.4% in 2001 to 62.3% by 2007. This limited performance history, especially during prior downturns, makes them more difficult for rating agencies to assess. In addition, limited documentation mortgages entail much more asymmetric information, because the rating agency must rely on the borrower's self report of their income, rather than verifiable information.

The finding that these characteristics are associated with poor performance ex-post, conditional on initial ratings, appears consistent with the prediction of Skreta and Veldkamp (2009) predicts that rating inflation should be greater for "opaque" securities, for which there is more residual uncertainty about fundamental security value. It is also consistent with Rajan, Seru and Vig (2008), which 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, several of the rating strategy variables are statistically significant in 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 subprime 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 (less than 1%) of our sample. Given this, and the endogeneity associated with the choice of rating agencies, we are reluctant to draw firm conclusions about the interpretation of the statistical significance of these "rating strategy" variables.

In addition, the last columns of Table 7 Panel A and B interact the main 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 estimate the same regression 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 are robust to this alternative specification.

[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]

7. Conclusions

We document features of MBS deals and ratings in the period leading up to the subprime crisis, and present evidence on the quality of credit ratings on these instruments. Our evidence suggests credit ratings issued on MBS did contain useful information, in the sense that they were correlated with fundamental measures of credit risk and credit enhancement in expected ways, and also correlated in the cross-section with ex-post deal performance.

However, we also identify a number of shortcomings in ratings during this period, relative to the benchmarks we consider. First, ratings exhibit significant time-series variation, in a way that does not seem easily accounted for by variation in the credit risk facing investors. Most strikingly, we find that at the peak of MBS issuance, when our model-projected default rate and other measures of credit risk were increasing significantly, ratings on subprime deals remained flat, while subordination on Alt-A deals actually decreased slightly. That this estimated erosion in ratings occurs during the peak of MBS issuance appears consistent with theoretical models where rating agencies trade off current profits against the reputational costs of revealed rating errors. Other interpretations are also possible, however.

Second, we present evidence that MBS ratings did not fully reflect publicly available data on credit risk. High-risk deals, as measured by our summary measure of credit risk, perform worse relative to their rating than do observably low-risk deals. These differences are quantitatively important, hold both cross-sectionally and in the time series, and also hold in vintage-level cross sectional regressions based only on data available well before the onset of the crisis. These deals experience higher ex-post defaults and investor losses, and are also more likely to be downgraded ex-post by rating agencies. Surprisingly, our simple summary statistic is often a more informative metric for ranking future MBS performance than the combined predictive power of subordination at two key attachment points, in a “horse race” type comparison. Given the significant body of evidence linking ratings to security prices, this suggests that these deals may also have been overpriced, leading to a relative oversupply of mortgage finance for loans with risky underwriting characteristics.

We find significant underperformance (relative to their ratings) amongst deals with a high fraction of loans which are difficult-to-evaluate, such as low-documentation and interest-only mortgages. This result is consistent with theoretical predictions from Skreta and Veldkamp (2009), and with previous evidence about low documentation deals presented by Rajan, Seru and Vig (2009). Finally, we find some correlations between the number of CRAs who rated the deal and the subsequent performance of the deal relative to its rating, consistent with Benmelech and Dlugosz (2009). Are these relationships indicative of explicit rating shopping amongst securities issuers? In this paper, we remain agnostic on this question, given the given that issuers’ choice of rating agencies is endogenous. However, we believe that investigating this question in more detail is an important topic for future research.

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Appendix A: Definitions of Variables

Variable	Description	Source
deal_wac	Weighted average coupon on deal, weighted by original face value of tranches.	ABSNet
excess_spread	Excess Spread on Deal. Defined as close_int - deal_wac.	ABSNet & LP
sub_amt_frac	AAA Subordination Percentage	BB
pool_qdate	Quarter of deal's first payment	BB
insurance_trust_frac	Fraction of deal value that has insurance	BB
close_int	Weighted interest rates on underlying mortgages at time of securitization, weighted by balance on loan.	LP
deal_no	Unique Deal Number	LP
Fico	Weighted Average FICO score on loans in deal	LP
Cltv	Weighted Average Combined LTV on loans in deal	LP
under_rat1	Weighted Average Debt-to-Income on loans in deal	LP
Subprime	Subprime Deal Identifier	LP
document_low	Weighted average percentage of loans that are document_low	LP
Investor	Weighted average percentage of loans that are investor	LP
Io	Weighted average percentage of loans that are io	LP
hpa_pre	Average Lagged 12-month House Price Apprecation	LP, OFHEO

Appendix B: Dataset construction [Note: This section is incomplete]

Our empirical analysis is based on a custom dataset combining loan-level and security level information, matched with house price and unemployment data. It is created by matching data from several sources[4]:

LoanPerformance

LoanPerformance (LP) is provided by FirstAmerican CoreLogic and contains loan-level data on the characteristics and ex-post performance for securitized subprime and Alt-A mortgages. (A separate dataset contains information on prime mortgages, although we do not make use of that data in this paper). It is the leading industry dataset of its type, and is widely used by investors, servicers and other industry participants. Data is collected from over 20 of the largest non-prime servicers, and LoanPerformance claims a market coverage of 93% of active nonprime deals. Coverage is however, somewhat lower in the earlier part of our sample, as documented in Figure 3 of this paper.

As well as loan-level data, LoanPerformance contains a deal identifier which allows us to aggregate the loans by issued deal. Moreover, LoanPerformance offers a concordance between the deal identifiers and security CUSIPs, which permits a one-to-many merge between LP deals and tranche-level data.

ABSNet

ABSNet is a product of Lewtan Technologies, a subsidiary of Standard & Poor's. It provides tranche, deal, ratings and performance data on a wide range of asset-backed securities (ABS). ABSNet's data on initial security and deal characteristics is predominately drawn from prospectuses filed by issuers. ABSNet has very comprehensive coverage of non-agency Residential Mortgage Backed Securities (RMBS) deals, covering 10,144 deals issued between 1990 and the present.

Bloomberg

We supplement our ABSNet security-level data with information from back-end Bloomberg downloads. Most importantly, Bloomberg provides some additional information about the cash flow characteristics of individual securities relative to ABSNet, allowing us to screen out double-counting of securities. This is detailed further below.

Macroeconomic data: House Prices and Unemployment

Based on the zip-code identifier in LP, each loan is matched to purchase-only house price index data from the Federal Home Financing Agency (FHFA, formerly known as OFHEO). We first match to a MSA-level price index. If the zip code is not part of an MSA, it is matched to the state-level purchase only FHFA house price index. In a few cases where neither MSA- or state-level matching is possible, we use the national FHFA index. We also match each loan to state-level unemployment data.

Merge Procedure [to complete]

This section describes the steps involved in cleaning and matching the different datasets to create our final merged security-loan-level dataset.

[4] The structure of our dataset is similar in most respects to the one independently created by Nadauld and Sherlund (2009), whose analysis is based on a smaller sample of 1,267 subprime deals from 1997-2007 matched with loan-level data from LoanPerformance.

Step 1: Bloomberg preparation

We first extract all security-level from Bloomberg for non-agency RMBS, identified as securities which are not flagged as "Agency Backed", and which have tickers that match either "RESB/C", "HOMEEQ", or "HELOC." We also drop tranches identified as "SC" or "STRUCTURED COLLATERAL", and deals with trust names ending in "I", "X", "A" or "W". Our advice from Bloomberg and understanding of these deals is that these are duplicates of cash deals, or deals collateralized by structured securities rather than physical mortgages. Consistent with this, none of these deals are linked to cash collateral via the security-level concordance provided to us by LoanPerformance.

To avoid double-counting and correctly calculate deal subordination below different rating levels, certain types of tranches, such as interest-only tranches with a nominal face value are recoded to be recorded as having a face value of zero.[5] Specifically, when calculating subordination below each tranche, we replace the face value of the following security types (as indicated by the "mtg_tranche_typ_long" field) with zero:

a. Notional ("NTL", "NOTIONAL_PRINCIPAL", "IO", INTEREST_ONLY_CLASS")
b. Prepayment Tranches ("PIP", "PREPAYMENT_PENALTY")
c. Exchangeable ("EXCH", "EXE")
d. Residual Tranches ("RESIDUAL", "R", "OC", "OVER-COLLATERALIZATION")
e. Subordinated ("SUBORDINATED_BOND")

Step 2: ABSNet preparation

Data is pulled from ABSNet screen-by-screen.

Step X: Aggregate LP loan-level data to the deal level

2.
3. Aggregate Loan Data

   First, LP loan-level data is aggregated to the deal level, weighted by loan value at time of securitization:

$$var_i = \frac{\sum_{j \epsilon deal\ i} var_{i,j} * close\_bal_j}{\sum_{j \epsilon deal\ i} close\_bal_j}$$

4. Pull Subprime and Alt-A securities from Bloomberg

   We keep all securities from Bloomberg that are listed as not being

[5] An interest-only tranche is created by stripping out the principal and interest payments from a set of mortgages into separate securities, known as IO and PO strips. In such situation, the notional value of both the IO and PO strip are recorded in Bloomberg as the face value underlying the strip. For purposes of calculating subordination levels, this double counts unless the face value of one of the securities is set to zero. (e.g. Imagine a deal backed by $1bn of mortgages, which consists of $900bn in PO bonds, $900bn in IO bonds, rated AAA, and an equity tranche of $100bn. The correct AAA subordination level in this example is 10%, but the raw sum of AAA securities would be $1.8bn (and the calculated subordination level erroneously equal to -80%) if we do not set the face value of either the IO or PO tranche equal to zero. This same argument applies to prepayment tranches, which receive unscheduled but not scheduled payments of principal.

5. Remove Structured Collateral tranches and doubled deals in BB

6. Account for nominal face values in BB

7. Determine Tranche Ratings from ABSNet
   We pull ratings history for all tranches listed in deals on ABSNet that are in the "Home Equity" or "Residential MBS" asset class, and determine the origination ratings by identifying the earliest rating on a tranche. When there are multiple ratings on a tranche, we identify the earliest rating across the CRAs, and then take all ratings that are issued within 200 days of the earliest rating. We then clean and equate the different CRAs' ratings to an equivalent scale.[6]
   Using this cleaned value, we can also determine the amount of downgrade for a particular tranche by taking the difference between the origination rating and the current rating.

8. Generate Loan-Level Predictions of Serious Delinquency using LP
   As described in the text, we use a 10% sample to recursively estimate the fraction of loans in a deal that will be seriously delinquent in 12 months. We then apply these coefficients to the underlying loans and aggregate to the deal level as in step 1.

9. Calculate Weighted Average Coupon using ABSNet
   For some tranches, an origination tranche coupon is not available in ABSNet. For these tranches, we use the earliest available coupon from ABSNet, so long as the date of the coupon is within 2 quarters of the origination date. If the date of the coupon is more than 2 quarters ahead of the origination date and the coupon is floating, then we estimate the margin on the tranche by differencing the six month LIBOR at the date of the coupon, and then estimate the original coupon by adding the six month LIBOR at the date of deal origination (obviously if the coupon is fixed, we can use the coupon regardless of date).

10. Merge the Data
   Finally, we merge the data from steps 1, 4, 5, 6 and 7 by CUSIP. We assume that Bloomberg has the maximum coverage of the MBS universe of tranches, and so we first require that any deal in the final dataset has tranche info from Bloomberg. Second, we eliminate any deals that do not have LoanPerformance underwriting and performance data. Finally, we ensure that the final deals contain at least one tranche with rating data from ABSNet.

   The LP Data contains 81,394 tranches and 4,715 deals (4641 with 12 month delinquency data).

11. The BB Data contains 157,993 tranches and 10,143 deals. ABSNet data contains 123,006 tranches and 9,114 deals.

12. Drop Out Negative Amortization Deals and Keep Deals from 2001-2007

Subprime/Alt-A Definition

There is no single consistent definition of subprime or Alt-A in the literature nor in the datasets which we use. Subprime is generally considered to include Residential B/C loans and Second Lien mortgages, whereas Alt-A includes those loans which would be called "exotic," namely low and no documentation, interest-only, and negative amortization mortgages. Of the three MBS

[6] We use the same measure for equating ratings between Fitch, S&P, Moody's and DBRS as Morgan (2002): AAA = Aaa = 1, AA+ = Aa1 = 2, etc.

datasets, LoanPerformance is the only dataset which identifies loans and deals as specifically subprime or Alt-A. Therefore, we consistently use LP's definition for subprime.

Reconciliation of Deal Counts

Since we are attempting to create a dataset which maximizes coverage of the non-agency MBS universe, it is of slight concern that the three datasets have different deal counts. The reason for this is two-fold: first, the total coverage of Bloomberg and ABSNet is much better prior to 2003 than LoanPerformance; second, as mentioned in the above, the definitions of Subprime and Alt-A are not necessarily consistent across the three vendors, such that Bloomberg and ABSNet's universe of non-Agency MBS may include significant amounts of private-label prime MBS.

Deal Structure

Since there are some tranches where ABSNet does not provide rating data, we also identify tranche labels that are considered "A-level", which are consistently rated at AAA by the CRAs. We do this by taking the *name* variable in the BB dataset and stripping the last word off of the string. This last word is the derived class name (*class_deriv)*, and we use regular expressions to identify if the tranche is named using a convention that labels it as an A-level tranche (i.e. "1A2" will be identified as A-level, whereas B2 will not). We use this as a backup in identifying AAA subordination data when ABSNet does not provide ratings data.

Credit Enhancement

Using the merged data, we can calculate the several aspects of credit enhancement identified in Section 2 of the paper. For subordination at the AAA attachment point, we calculate:

$$subordination_{aaa} = 1 - \frac{\sum mtg\_face\_amt_{aaa}}{\sum mtg\_face\_amt},$$

where *mtg_face_amt* is the original face value of the tranches, as identified in the Bloomberg dataset. For a deal's excess spread, we calculate:

$$excess\ spread_i = close\_int_i - deal\_wac_i.^{7}$$

Insurance is provided in the Bloomberg data, and is marked on certain tranches with the *mtg_cred_prov* variable. If this variable is present, then the tranche is wrapped with insurance. We generate both a dummy variable for presence of insurance on the deal (*insurance_trust*), as well as a variable measuring the percentage size of the tranche with insurance (*insurance_trust_frac)*.

Other Deal Characteristics

To get a measure for geographic density, we create a Herfindahl-Hirschman Index measure using the LP data, measuring the percentage of loans in a deal originated in each state:

$$state\_hhi = \sum_{j \in states} \left(\frac{\sum close\_bal_j}{deal\_amt}\right)^2$$

[7] For some tranches, an origination coupon is not available. For these tranches, we use the earliest available coupon from ABSNet, so long as the date of the coupon is within 2 quarters of the origination date. If the date of the coupon is more than 2 quarters ahead of the origination date and the coupon is floating, then we estimate the margin on the tranche by differencing the six month LIBOR at the date of the coupon, and then estimate the original coupon by adding the six month LIBOR at the date of deal origination.

Figure 1: Net credit rating downgrades by vintage

Figure plots net average nonprime MBS ratings revisions by issuance quarter between Q1:2001 and Q4: 2007. Y-axis measures the average net number of notches that MBS issued in quarter have been downgraded between issuance and August 2009, weighted by security original face value. [e.g. A security downgraded by S&P 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-.] A negative value means securities issued in a particular quarter have on average been upgraded. For securities with multiple ratings, the net rating change is a simple average across ratings. Amongst the two largest rating agencies, Moody's ratings are based on a 21 notch scale (Aaa to C), while S&P's ratings are based on a 22 notch scale (AAA to D).

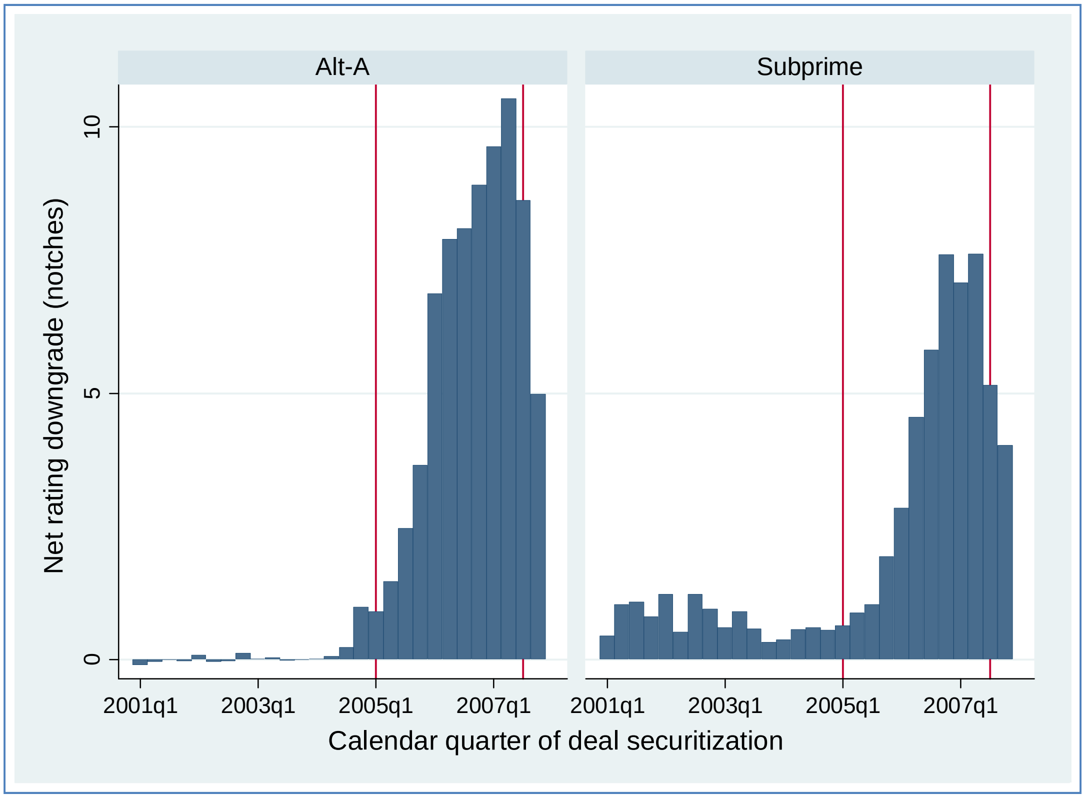

Figure 2: Structure of a non-agency MBS deal

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. [Source: Moody's].

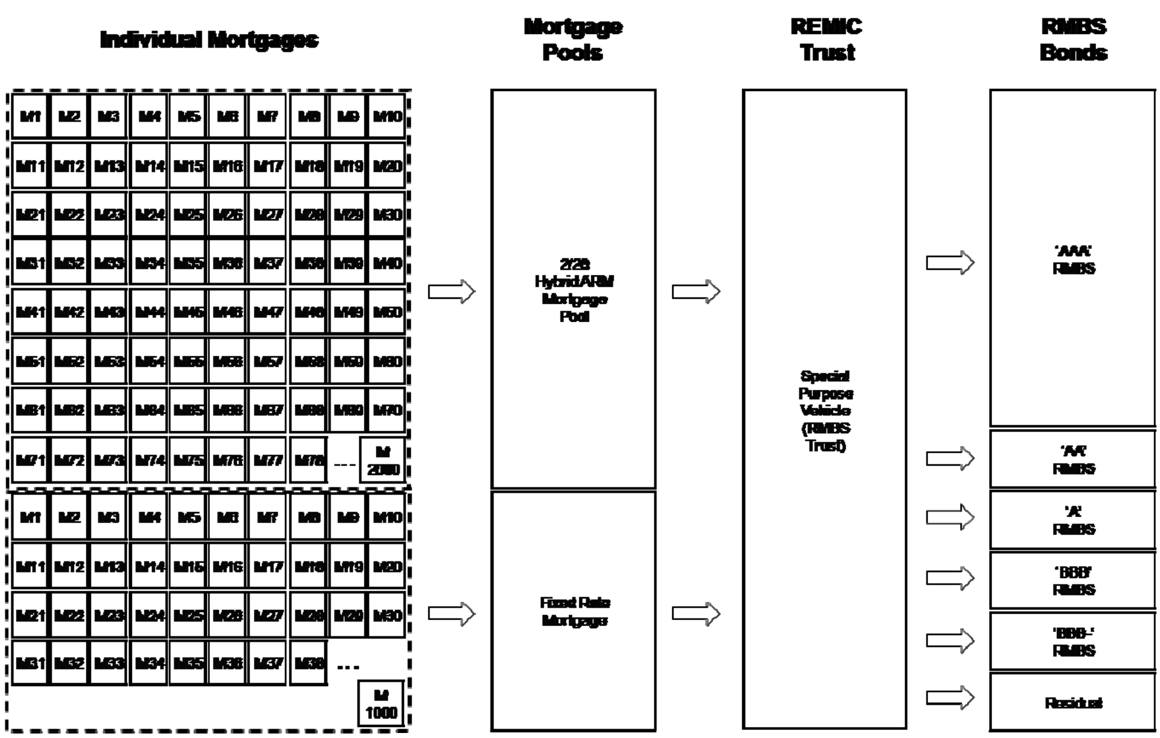

Figure 3: Evolution of Subprime and Alt-A MBS Issuance

The figure plots the number and total face value of subprime and Alt-A securities issuance by year-quarter over the period 2000-2008, based on data from Bloomberg, ABSNet and LoanPerformance. It also plots total issuance volume based on the industry publication Inside Mortgage Finance, which documents that our data captures a large fraction of total MBS origination volume.

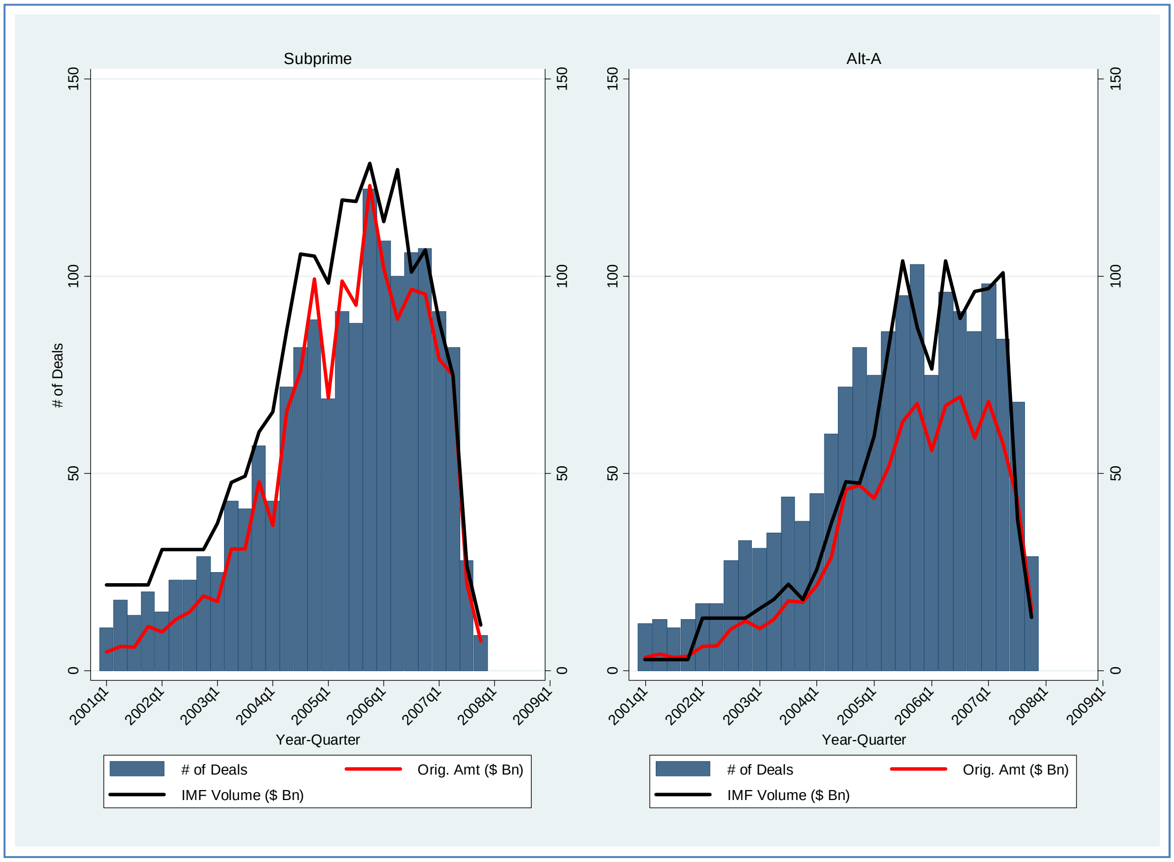

Figure 4: Evolution of subordination levels, subprime and Alt-A deals

This figure plots the average fraction of subprime and Alt-A deals below three different rating leves, AAA, A and BBB. Subordination is defined as 1 – [face value of securities at that class or a more senior class] / [face value of mortgages in the deal], by year-quarter between 2001 and 2007. 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.

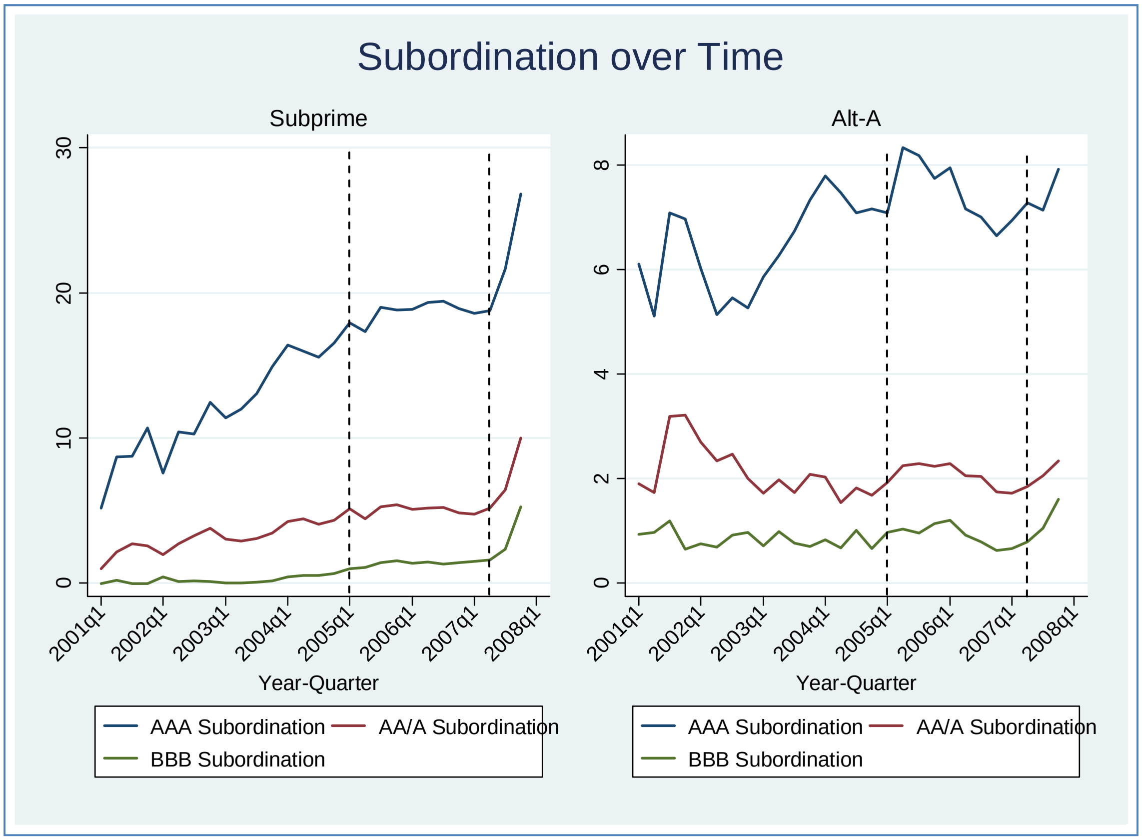

Figure 5: Observed and predicted 90+ day delinquency at 12 months

Figure plots average projected default rate by year-quarter vintage from the baseline logit regression model and the realized ex-post 12-month default rate for deals from that vintage.

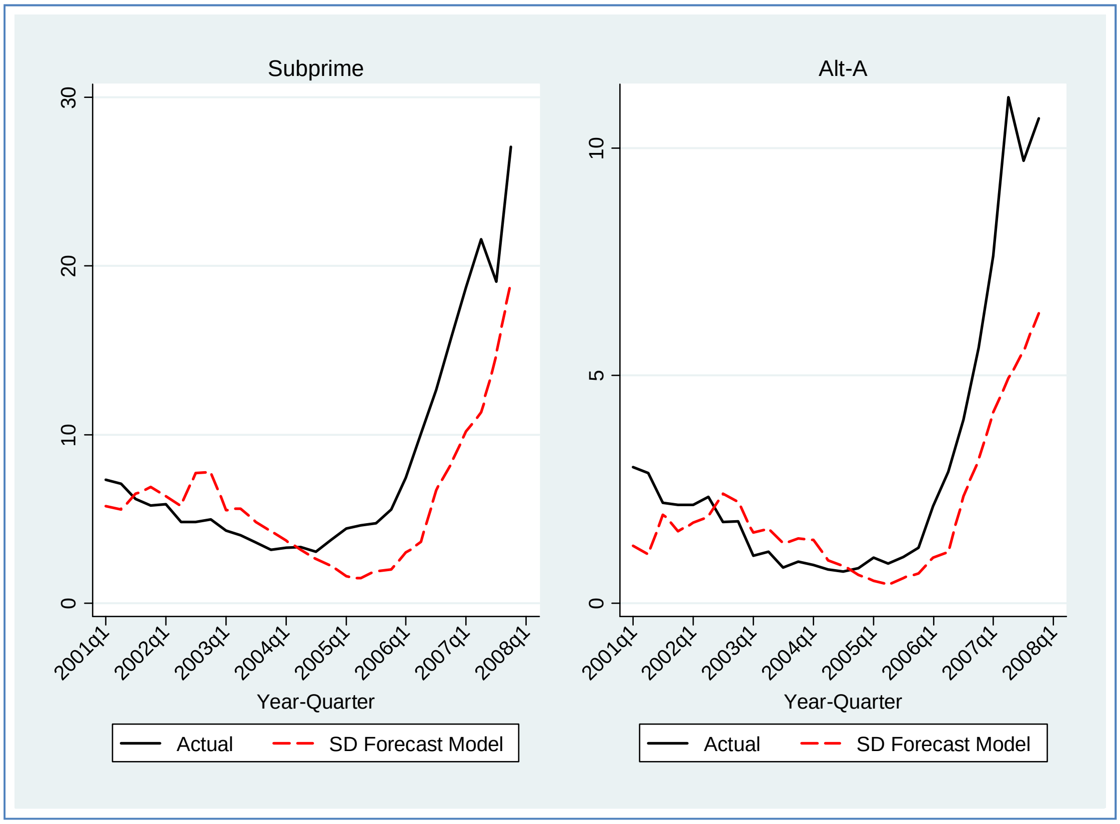

Figure 6: Predicted versus actual subordination

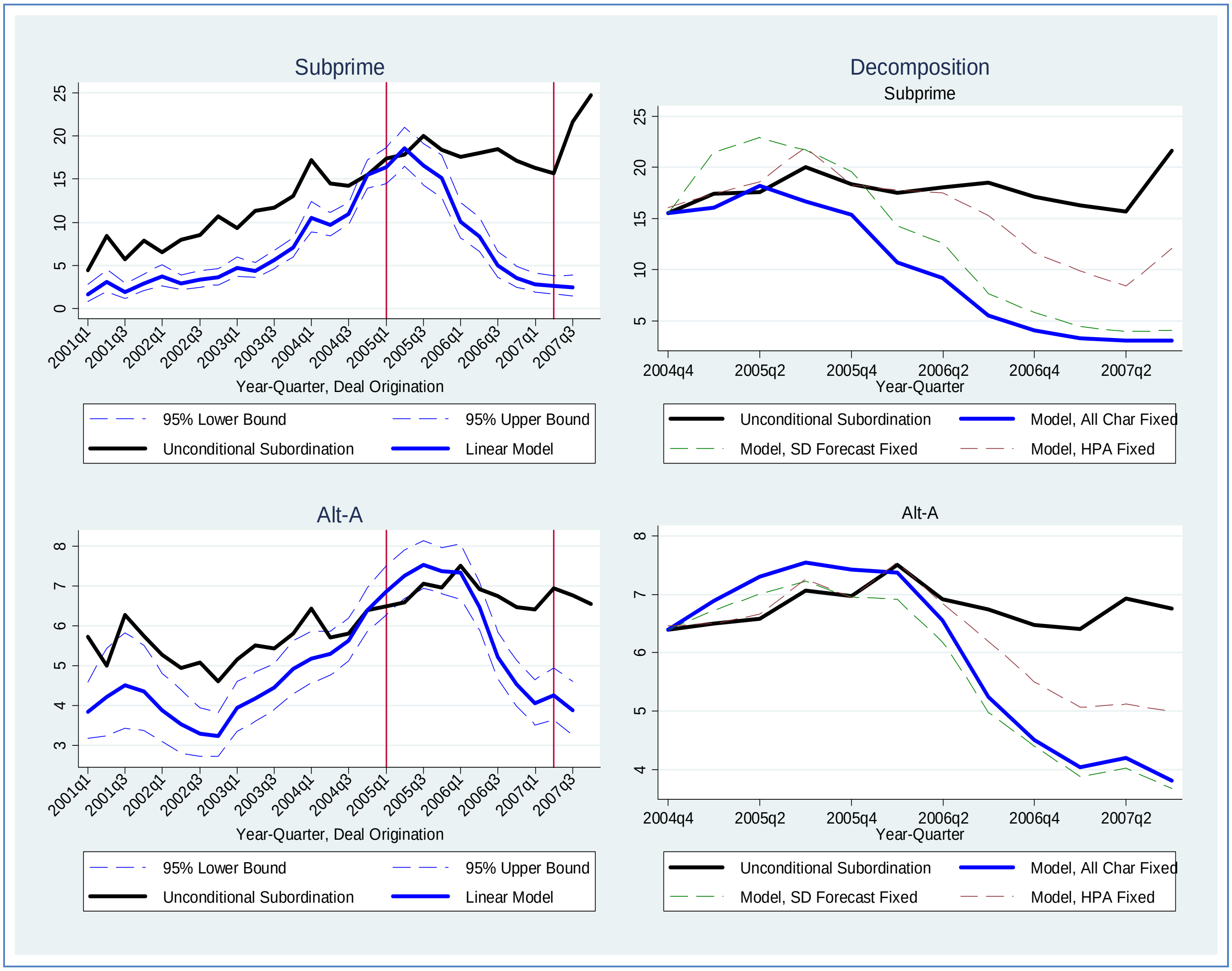

Table 1. Deal characteristics

Table provides summary statistics for our sample of 3,144 subprime and Alt-A deals issued between 2001 and 2007. Data is drawn from ABSNet, Bloomberg and LoanPerformance. Sample excludes negative amortization deals.

	Subprime	**Alt-A**	**All**
Number of deals	1607	1537	3144
Total number of securities	26430	33525	59955
Securities per deal, median	17	19	18
AAA securities per deal, median	5	10	6
Credit enhancement			
Percent of deals with bond insurance	14.0	8.8	11.5
Average value of insurance (%FV)	5.0	1.9	3.5
Excess spread at origination (%), median	3.8	1.2	2.6
Excess spread at origination (%), average	4.1	1.4	2.8
Deal size ($m):			
Mean	896	595	749
25^{th} percentile	509	313	391
50^{th} percentile	790	487	631
75^{th} percentile	1120	756	960
Fraction of AAA (%)			
Mean	82.4	93.1	87.6
25^{th} percentile	79.1	92.4	81.4
50^{th} percentile	81.7	93.9	89.3
75^{th} percentile	84.5	95.0	94.1
Fraction of non-AAA securities (mean, %)			
AA rating	7.9	3.4	5.7
A rating	4.9	1.5	3.2
BBB rating	3.5	1.0	2.3
BB rating	0.8	0.4	0.6
Unrated or OC	1.3	2.0	1.7
Number of CRAs that rated the deal (%)			
Rated by one rating agency	0.3	0.4	0.3
Rated by two rating agencies	48.1	83.0	65.1
Rated by three rating agencies	45.1	16.5	31.1
Rated by four rating agencies	6.5	0.2	3.4

Table 2. Mortgage characteristics

Table presents summary statistics for the 12.1m individual mortgages underlying the 3,144 deals summarized in Table 1. Data is drawn from LoanPerformance.

	Subprime	Alt-A	All
Loan amounts			
Number of loans, total	8,810,111	3,263,992	12,074,103
Number of loans per deal, average	5,506	2,114	3,840
Loan size (average)	256,652	435,641	325,517
Combined loan-to-valuation ratio (%)			
Average (%, value-weighted)	85.3	80.8	83.6
10th percentile	68.0	59.3	64.3
50th percentile	87.3	80.0	85.0
90th percentile	100.0	100.0	100.0
% missing	0.0	0.0	0.0
Junior-lien mortgages (% of deal size, avg)	6.8	0.4	4.3
FICO scores			
Average (value-weighted)	625	706	656
10th percentile	545	646	563
50th percentile	626	708	660
90th percentile	708	776	754
% Missing	0.4	0.7	0.5
Debt-to-income ratio			
Average (value-weighted)	41.1	37.2	40.0
10th percentile	28.3	25.0	27.3
50th percentile	43.0	38.4	41.7
90th percentile	50.0	47.4	50.0
% Missing	28.5	56.3	39.2
Interest only loans			
% IO mortgages	17.4	54.0	31.5
Number of deals with IO > 1%	1,136	1,215	2,351
Number of deals with IO > 75%	32	485	517
Documentation (%):			
Full	59.1	28.4	47.3
Low	40.3	65.0	49.8
No	0.4	5.8	2.5
Missing	0.2	0.8	0.4

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	63	90	166	286	370	422	210	1,607
Deal size, average ($m)	448	633	767	971	1,040	908	874	896
Fraction of AAA securities (%)								
Average	90.1	88.2	86.1	83.5	80.5	80.4	80.3	82.4
Median	90.2	86.5	84.6	83.0	80.6	80.1	79.6	81.7
Excess spread (median, %)	5.5	6.3	5.8	5.1	3.5	2.8	2.7	3.8
Fraction deals with bond insurance	39.7	35.6	18.7	19.2	9.2	5.9	11.4	14.0
Percent deals rated by all three CRAs	42.9	48.9	63.9	61.2	60.5	43.1	33.8	0.3
Loan characteristics, value weighted								
CLTV (%, average)	81.9	82.6	83.0	84.0	85.6	86.8	86.5	85.3
Junior-lien mortgages (average % of deal)	13.4	9.0	4.4	3.1	5.3	9.5	10.3	6.8
FICO, average	611	614	622	623	631	630	631	625
Debt-to-income (%), average	35.8	35.2	38.0	38.7	40.0	41.3	41.3	41.1
Interest-only mortgages (avg % of deal)	0.0	0.3	2.4	11.4	28.0	21.4	16.4	17.4
Low/no-doc mortgages (% of deal, avg)	24.8	30.2	33.6	36.8	42.4	46.0	45.1	40.7
12-month-ended HPA (OFHEO)	9.0	8.3	8.8	15.6	17.7	12.5	3.0	12.0

Panel B. Alt-A deals

	2001	2002	2003	2004	2005	2006	2007	All
Deal characteristics								
Number of deals	49	95	148	259	359	348	279	1,537
Deal size, average ($m)	300	377	398	554	631	723	661	595
Fraction of AAA securities (%)								
Average	93.7	94.6	93.7	93.3	92.6	92.8	92.9	93.1
Median	94.3	95.0	95.0	94.3	93.4	93.5	93.7	93.9
Excess spread (median, %)	2.4	2.4	1.7	1.4	1.0	1.0	1.0	1.2
Fraction deals with bond insurance	28.6	15.8	11.5	8.1	7.8	4.6	8.6	8.8
Percent deals rated by all three CRAs	32.7	10.5	4.1	4.2	12.0	25.3	29.4	0.4
Loan characteristics, value weighted								
CLTV (%, average)	79	79	76	80	80	82	81	81
Junior-lien mortgages (average % of deal)	0.1	0.1	0.0	0.2	0.1	0.1	0.7	0.4
FICO, average	698	699	706	708	712	708	711	706
Debt-to-income (%), average	18.6	21.4	22.6	26.6	29.0	29.0	29.7	37.2
Interest-only mortgages (avg % of deal)	0.4	2.4	12.2	45.9	58.4	60.7	62.3	54.0
Low/no-doc mortgages (% of deal, avg)	66.3	63.1	64.5	63.2	65.8	77.4	79.3	70.9
12-month-ended HPA (OFHEO)	10.3	9.1	9.1	16.7	18.4	12.7	1.8	12.0

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 ex-ante historical samples to construct a projected default rate for each deal; see text for details). 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, foreclosure, prepaid with loss or REO) 12 months after origination. =0 otherwise.

Underwriting variables	
CLTV	0.000925***
	(0.000106)
FICO	-0.000340***
	(8.89e-06)
12-month trailing HPA	-0.00173***
	(0.000185)
Balloon loan	3.86e-05***
	(5.18e-06)
Low Doc	0.000172***
	(9.69e-06)
No Doc	0.000240***
	(1.54e-05)
Investor	0.000131***
	(8.79e-06)
DTI	0.000320***
	(1.73e-05)
DTI Missing	8.19e-05***
	(9.58e-06)
Cashout Refinance	-0.000115***
	(8.25e-06)
ln(loan amount)	0.0161***
	(0.00148)
Prepayment Penalty	0.000117***
	(5.38e-06)
Local unemployment rate	0.000175
	(0.000268)
Spread at Origination	0.00392***
	(0.000989)
Other covariates	
Year-half dummies	yes
N (10% LP sample)	1309495
Unconditional Mean of Serious Delinquency	0.0602
Pseudo R-Squared	0.1497

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 publicly available 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				
ln(1+projected default rate)	0.751***	0.680**	0.727***	0.651***
	(0.231)	(0.254)	(0.231)	(0.186)
$\ln(1+\text{projected default rate})^2$	0.0551	0.0723	-0.130	-0.153**
	(0.0676)	(0.0705)	(0.0870)	(0.0707)
Joint significance: F-Test (p-value)	0.0000***	0.0000***	0.0000***	0.0006***
Other deal characteristics				
Bond insurance (1=yes)	-0.473***	-0.478***	-0.0250	0.00370
	(0.100)	(0.100)	(0.0395)	(0.0376)
Fraction of deal with bond insurance	-0.0104**	-0.0104**	-0.00331	-0.00414*
	(0.00432)	(0.00426)	(0.00245)	(0.00223)
Weighted average coupon rate	0.00811	0.0201	-0.0634***	-0.0231
	(0.0408)	(0.0405)	(0.0145)	(0.0148)
Weighted mortgage interest rate	0.0468*	0.0498**	0.0681*	0.0263
	(0.0231)	(0.0233)	(0.0368)	(0.0341)
Geographic concentration of loans	1.897***	1.677***	0.406***	0.399***
	(0.212)	(0.263)	(0.134)	(0.117)
Year x quarter dummies	Yes	Yes	Yes	Yes
F-test: ratings decline over 2005-07? (p-value)[a]	0.0001***	0.0005***	0.0054***	0.759
Include aggregated loan-level variables	No	Yes	No	Yes
Joint significance: F-Test (p-value)		0.144000		0.0000***
N	1607	1607	1537	1537
R^2	0.529	0.531	0.193	0.281

[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 5: 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
ln(1+% subordination below AAA)		0.285***		0.112***	0.112***
		(0.0396)		(0.0340)	(0.0305)
ln(1+% subordination below BBB-)		0.110***		0.0955***	0.0645***
		(0.0211)		(0.0157)	(0.0144)
ln(1+projected default rate)			1.076***	0.941***	1.004***
			(0.0566)	(0.0622)	(0.0567)
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	1607	1607	1607	1607	1607
R^2	0.092	0.275	0.483	0.521	0.862

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
ln(1+% subordination below AAA)		0.356***		0.198***	0.0505
		(0.0531)		(0.0378)	(0.0344)
ln(1+% subordination below BBB-)		-0.201***		-0.144***	-0.0960***
		(0.0638)		(0.0423)	(0.0241)
Projected default rate			1.556***	1.470***	1.523***
			(0.0604)	(0.102)	(0.0422)
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: Deal-level covariates [p-value]					0.0000***
N	1537	1537	1537	1537	1537
R^2	0.330	0.394	0.618	0.640	0.893

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
ln(1+% subordination below AAA)	0.112***	0.244***	0.112***	0.118***
	(0.0340)	(0.0439)	(0.0305)	(0.0325)
ln(1+% subordination below BBB-)	0.0955***	0.0832***	0.0645***	0.0552***
	(0.0157)	(0.0187)	(0.0144)	(0.0134)
ln(1+projected default rate)	0.941***		1.004***	0.837***
	(0.0622)		(0.0567)	(0.0522)
Other deal characteristics				
Bond insurance (1=yes)	3.35e-05	0.000472	0.000129	0.00554
	(0.0438)	(0.0458)	(0.0334)	(0.0323)
Fraction of deal with bond insurance	0.00177*	0.00223**	0.00131*	0.00133**
	(0.000872)	(0.000936)	(0.000664)	(0.000623)
Weighted average coupon rate	-0.0243	-0.123***	-0.0112	-0.0500**
	(0.0222)	(0.0306)	(0.0221)	(0.0190)
Weighted mortgage interest rate	-0.0762***	-0.0728***	-0.130***	-0.122***
	(0.0105)	(0.0181)	(0.0152)	(0.0154)
Geographic concentration of loans	0.475**	-0.454*	0.0635	0.0540
	(0.194)	(0.238)	(0.203)	(0.196)
Rating strategy				
One Rating		0.509***	0.213***	0.305***
		(0.126)	(0.0343)	(0.0392)
Two Ratings		-0.0475***	0.0108	0.0505*
		(0.0171)	(0.0149)	(0.0268)
Four Ratings		0.0357	0.113***	0.106***
		(0.0274)	(0.0290)	(0.0275)
Aggregated loan-level covariates				
LTV		0.000992	0.00889***	0.00715***
		(0.00350)	(0.00188)	(0.00169)
FICO		-0.00174	0.000279	0.000302
		(0.00103)	(0.000469)	(0.000486)
HPA		-0.0184**	-0.00279	-0.00245
		(0.00745)	(0.00815)	(0.00753)
IO		-0.00133*	-0.000429	-0.000990
		(0.000766)	(0.000515)	(0.000765)
Low doc		0.00725***	0.00681***	0.00327***
		(0.000873)	(0.000656)	(0.000852)
Investor		0.00756**	0.00430*	0.0212***
		(0.00334)	(0.00230)	(0.00454)
Loan level covariate interactions				
Projected delinquency rate * boom				0.317***
				(0.0939)
IO * boom				0.00129
				(0.000776)
Low doc * boom				0.00568***
				(0.00115)
Investor * boom				-0.0216***
				(0.00507)
Less Than Three Ratings* boom				-0.0667**
				(0.0295)
Year x quarter dummies	yes	yes	yes	yes
N	1607	1607	1607	1607
R^2	0.521	0.389	0.594	0.613

Table 7 (cont…)

Panel B: Alt-A deals

Include covariates	No	Yes	Yes	Yes
Credit boom interactions	No	No	No	Yes
ln(1+% subordination below AAA)	0.198***	0.149***	0.0505	0.0553*
	(0.0378)	(0.0415)	(0.0344)	(0.0317)
ln(1+% subordination below BBB-)	-0.144***	-0.161***	-0.0960***	-0.0794***
	(0.0423)	(0.0430)	(0.0241)	(0.0234)
ln(1+projected default rate)	1.470***		1.523***	1.503***
	(0.102)		(0.0422)	(0.0610)
Other deal characteristics				
Bond insurance (1=yes)	-0.0120	0.140***	0.0237	0.0261
	(0.0358)	(0.0363)	(0.0329)	(0.0320)
Fraction of deal with bond insurance	-0.00112	-0.00417***	-0.00221**	-0.00192*
	(0.00117)	(0.00149)	(0.00104)	(0.000992)
Weighted average coupon rate	-0.0264**	-0.0130	0.0105	0.00340
	(0.0124)	(0.0164)	(0.00964)	(0.0106)
Weighted mortgage interest rate	0.0613	0.319***	0.0184	0.00422
	(0.0428)	(0.0448)	(0.0265)	(0.0280)
Geographic concentration of loans	-0.133	0.153	-0.239**	-0.241**
	(0.107)	(0.104)	(0.101)	(0.0953)
Rating strategy (omitted category = one rating)				
One Rating		0.127	-0.0161	-0.0581
		(0.126)	(0.0343)	(0.0392)
Two Ratings		0.0998***	0.0366*	0.00127
		(0.0171)	(0.0149)	(0.0268)
Four Ratings		0.0620	0.0620	0.0976
		(0.0274)	(0.0290)	(0.0275)
Aggregated loan-level covariates				
LTV		0.0260***	0.0188***	0.0182***
		(0.00424)	(0.00130)	(0.00160)
FICO		-0.000903***	0.00143***	0.00145***
		(0.000261)	(0.000230)	(0.000219)
HPA		-0.00658	0.00857	0.00751
		(0.00614)	(0.00539)	(0.00550)
IO		0.00220***	0.00155**	-0.000256
		(0.000772)	(0.000608)	(0.000649)
Low doc		0.00531***	0.00290***	0.00267***
		(0.001000)	(0.000792)	(0.000839)
Investor		0.00271**	0.00190**	-0.000272
		(0.00118)	(0.000814)	(0.00111)
Loan level covariate interactions				
Projected delinquency rate * boom				0.0724
				(0.115)
IO * boom				0.00252***
				(0.000878)
Low doc * boom				0.000607
				(0.00128)
Investor * boom				0.00420**
				(0.00197)
Less Than Three Ratings * boom				0.0382
				(0.0385)
Year x quarter dummies	yes	yes	yes	yes
N	1537	1537	1537	1537
R^2	0.64	0.565	0.741	0.747

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				
ln(1+% subordination below AAA)	-0.923***	-0.902***	-0.0465	-0.566*
	(0.246)	(0.258)	(0.227)	(0.282)
ln(1+% subordination below BBB-)	0.630***	0.442**	1.489***	1.640***
	(0.206)	(0.178)	(0.420)	(0.440)
ln(1+projected default rate)	0.817*	0.748	2.595***	3.066***
	(0.472)	(0.597)	(0.909)	(0.948)
Other deal characteristics				
Bond insurance (1=yes)	-0.379	-0.309*	-0.707**	-0.621*
	(0.226)	(0.160)	(0.342)	(0.345)
Fraction of deal with bond insurance	0.00798	0.00488	0.0243***	0.0210***
	(0.00557)	(0.00592)	(0.00634)	(0.00588)
Weighted average coupon rate	-0.421	-0.471*	0.0734	0.154
	(0.314)	(0.256)	(0.111)	(0.102)
Wtd avg mortgage interest rate	1.234***	0.986***	-0.270	-0.318
	(0.331)	(0.339)	(0.360)	(0.387)
Geographic concentration of loans	6.441***	5.566***	-0.415	-1.354
	(2.015)	(1.871)	(1.077)	(1.109)
Rating strategy (omitted category = three ratings)				
One Rating		5.130		-0.723*
		(3.599)		(0.367)
Two Ratings		-0.294**		-0.391
		(0.130)		(0.259)
Four Ratings		0.158		0.833
		(0.248)		(1.332)
Aggregated loan-level covariates				
LTV		0.0377		0.0290*
		(0.0237)		(0.0162)
FICO		0.000947		0.00499***
		(0.00208)		(0.00163)
HPA		-0.166**		0.109**
		(0.0713)		(0.0500)
IO		0.00183		0.00780
		(0.00550)		(0.00600)
Low doc		0.0444***		0.0151***
		(0.0133)		(0.00521)
Investor		0.0443***		0.0115
		(0.0151)		(0.00740)
Year x quarter dummies	yes	yes	yes	yes
N	1607	1607	1537	1537
R^2	0.612	0.654	0.674	0.685

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 & deal covariates	rating only	model only	model & rating	model, rating & deal covariates
Deal subordination below AAA	0.0468*		0.0337	0.0397	0.389***		0.290***	0.0689
	(0.0264)		(0.0328)	(0.0263)	(0.0676)		(0.0672)	(0.0502)
Deal subordination below BBB-	0.164***		0.163***	0.124***	-0.129**		-0.0971**	-0.0402**
	(0.0260)		(0.0258)	(0.0191)	(0.0503)		(0.0374)	(0.0189)
Projected default rate		0.157***	0.0677	0.369***		0.972***	0.841***	0.684***
		(0.0546)	(0.0728)	(0.0668)		(0.139)	(0.145)	(0.0726)
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]				0.0000***				0.0000***
N	1567	1567	1567	1567	1461	1461	1461	1461
R^2	0.389	0.361	0.390	0.516	0.297	0.344	0.383	0.611

B. Dependent variable: 24 month 90+ delinquency rate

	Subprime				Alt-A			
	rating only	model only	model & rating	model, rating & deal covariates	rating only	model only	model & rating	model, rating & deal covariates
Deal subordination below AAA	0.228***		0.0751**	0.0769**	0.397***		0.279***	0.106**
	(0.0303)		(0.0338)	(0.0284)	(0.0603)		(0.0534)	(0.0398)
Deal subordination below BBB-	0.107***		0.0956***	0.0700***	-0.164***		-0.113**	-0.0675**
	(0.0192)		(0.0151)	(0.0140)	(0.0577)		(0.0443)	(0.0287)
Projected default rate		0.930***	0.829***	0.942***		1.260***	1.146***	1.061***
		(0.0553)	(0.0761)	(0.0641)		(0.143)	(0.0704)	(0.0677)
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]				0.0000***				0.0000***
N	1594	1594	1594	1594	1498	1498	1498	1498
R^2	0.224	0.397	0.425	0.521	0.388	0.513	0.551	0.695

C. Dependent variable: 90+ delinquency rate to date

	Subprime				Alt-A			
	rating only	model only	model & rating	model, rating & deal covariates	rating only	model only	model & rating	model, rating & deal covariates
Deal subordination below AAA	0.137***		0.0531	0.0525*	0.399***		0.291***	0.104***
	(0.0297)		(0.0334)	(0.0303)	(0.0475)		(0.0471)	(0.0312)
Deal subordination below BBB-	0.0566**		0.0524**	0.0374**	-0.118*		-0.0841*	-0.0412
	(0.0205)		(0.0195)	(0.0163)	(0.0595)		(0.0465)	(0.0290)
Projected default rate		0.505***	0.435***	0.653***		1.042***	0.911***	0.731***
		(0.0644)	(0.0818)	(0.0834)		(0.0868)	(0.0881)	(0.0713)
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]				0.0000***				0.0000***
N	1567	1567	1567	1567	1461	1461	1461	1461
R^2	0.081	0.136	0.149	0.282	0.304	0.384	0.434	0.674

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	0.341	0.409	0.309	0.195	0.026	0.402	0.260	0.092
Baseline & rating								
Subordination below AAA	0.343**	0.0852	0.104	0.236***	0.369**	0.512**	0.474***	0.285***
	(0.0606)	(0.0503)	(0.0884)	(0.0216)	(0.0913)	(0.137)	(0.0634)	(0.0393)
Subordination below BBB-	-0.260	-0.0221	0.178**	0.0405	0.0448	-0.0294	0.0403	0.110***
	(0.314)	(0.184)	(0.0530)	(0.0264)	(0.0269)	(0.0494)	(0.0673)	(0.0209)
R^2	0.520	0.424	0.359	0.365	0.154	0.487	0.559	0.275
Baseline & model prediction								
Projected delinquency rate	1.072***	0.864***	0.718***	0.927***	1.428***	0.825**	1.224***	1.076***
	(0.0249)	(0.113)	(0.106)	(0.129)	(0.0202)	(0.228)	(0.0252)	(0.0561)
R^2	0.856	0.716	0.516	0.413	0.449	0.550	0.674	0.483
Baseline & rating & model prediction								
Subordination below AAA	0.00254	-0.0372	0.0423	0.146**	0.116	0.331*	0.196*	0.112***
	(0.0817)	(0.0526)	(0.0875)	(0.0390)	(0.0561)	(0.136)	(0.0767)	(0.0337)
Subordination below BBB-	0.0312	-0.00253	0.165**	0.0662**	0.0561	-0.0191	0.0427	0.0955***
	(0.0288)	(0.101)	(0.0471)	(0.0143)	(0.0286)	(0.0347)	(0.0647)	(0.0156)
Projected delinquency rate	1.070***	0.889***	0.684***	0.753***	1.327***	0.697*	0.942***	0.941***
	(0.106)	(0.146)	(0.109)	(0.127)	(0.0340)	(0.275)	(0.0275)	(0.0617)
R^2	0.856	0.719	0.537	0.490	0.471	0.582	0.713	0.521
N	63	90	166	286	370	422	210	1607

Table 10 (cont…)

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

	Vintage							All Years
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	
B. Alt-A deals								
Baseline (just deal controls; same as Column 1 of Table 6)								
R^2	0.779	0.696	0.598	0.450	0.338	0.368	0.273	0.330
Baseline & rating								
Subordination below AAA	-0.0667	0.0894	0.0514	0.167*	0.524***	0.642***	0.543**	0.356***
	(0.167)	(0.117)	(0.0774)	(0.0579)	(0.0528)	(0.102)	(0.140)	(0.0527)
Subordination below BBB-	-0.104	-0.0396	-0.106	-0.142**	-0.114*	-0.244	-0.394	-0.201***
	(0.118)	(0.154)	(0.0633)	(0.0345)	(0.0399)	(0.145)	(0.229)	(0.0632)
R^2	0.786	0.699	0.603	0.496	0.547	0.451	0.343	0.394
Baseline & model prediction								
Projected delinquency rate	0.506	1.180***	1.264***	0.940**	1.463**	1.711***	1.989***	1.556***
	(0.266)	(0.176)	(0.150)	(0.176)	(0.395)	(0.223)	(0.0432)	(0.106)
R^2	0.818	0.809	0.775	0.612	0.534	0.622	0.706	0.618
Baseline & rating & model prediction								
Subordination below AAA	-0.00529	0.0250	0.0771	0.104*	0.401***	0.284***	0.0311	0.198***
	(0.156)	(0.0358)	(0.0513)	(0.0440)	(0.0659)	(0.0361)	(0.104)	(0.0375)
Subordination below BBB-	-0.0683	-0.107	-0.0550	-0.0778	-0.118*	-0.118	-0.205	-0.144***
	(0.0947)	(0.171)	(0.0535)	(0.0446)	(0.0493)	(0.0935)	(0.104)	(0.0419)
Projected delinquency rate	0.483	1.212**	1.268***	0.872***	1.090**	1.560***	1.972***	1.470***
	(0.319)	(0.234)	(0.136)	(0.147)	(0.322)	(0.185)	(0.0856)	(0.101)
R^2	0.820	0.814	0.780	0.628	0.644	0.637	0.719	0.640
N	49	95	148	259	359	348	279	1537