Discussion paper

MBS RATINGS AND THE MORTGAGE CREDIT BOOM

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MBS Ratings and the Mortgage Credit Boom

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. The fraction of highly-rated securities in each deal is decreasing in mortgage credit risk (measured either ex-ante or ex-post), suggesting ratings contain useful information for investors. However, we also find evidence of significant time-variation in risk-adjusted credit ratings, including a progressive decline in standards around the MBS market peak between the start of 2005 and mid-2007. Conditional on initial ratings, we observe underperformance (high mortgage defaults and losses, and large rating downgrades) amongst deals with observably higher-risk mortgages based on a simple ex-ante model, and deals with a high fraction of opaque low-documentation loans. These findings hold over the entire sample period, not just for deal cohorts most affected by the crisis.

Keywords: Credit Rating Agencies, Subprime Crisis, Mortgage-Backed Securities

JEL Classifications: G01, G21, G24

Mistakes by credit rating agencies (CRAs) are often cited as one of the causes of the recent 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 high mortgage defaults, however, many MBS originally rated investment-grade now trade significantly below par, and have experienced large rating downgrades and even losses. Figure 1 plots net rating revisions on subprime and Alt-A MBS issued since 2001. While net rating revisions are small for earlier vintages, MBS issued since 2005 have experienced historically large downgrades, by 3-10 rating notches on average, depending on the vintage.

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. US Senate, 2010; White, 2009; Fons, 2008).[1] In their defense however, rating agencies argue that recent MBS performance primarily reflects a set of large, unexpected shocks, including an unprecedented decline in home prices, and a financial crisis, events which surprised most market participants. CRAs also point to warnings made by them before the crisis about increasing risk amongst subprime MBS, and argue that 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). The New York Attorney General is reportedly currently investigating eight large MBS issuers regarding claims these firms manipulated ratings through rating shopping, by reverse engineering rating models, sometimes with the help of former CRA employees, by misreporting information on MBS collateral, and other means (New York Times, 2010).

[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 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

Motivated by this debate, this paper studies credit ratings on subprime and Alt-A residential MBS deals issued from 2001-07, the period leading up to the crisis. Our analysis is based on a novel dataset of 3,144 MBS deals matched by us with security- and loan-level data. These deals represent around 60,000 securities and 12.1m loans, covering nearly 90% of deals issued during this period.

Our basic research question: How well did initial credit ratings summarize the variation in MBS default risk across this sample of deals? CRAs state that one of their key goals is for each letter rating to have a consistent interpretation regardless of the type of security or the time the rating opinion is issued. (See Section 1 for a detailed discussion). Motivated by these statements, we study the consistency of MBS ratings in two dimensions: (i) through time, and (ii) across deals from a given vintage backed by different types of loans.

Our main unit of analysis is an MBS *deal*, which is a set of structured bonds linked to a common pool (or pools) of mortgages. Ratings for an MBS deal are typically described in terms of the "subordination level" or "attachment point" of each rating, which is the fraction of the deal junior to the bonds of that letter rating. For example, if a deal consists of $1bn of mortgages, and only the most senior $850m of bonds are rated triple-A, subordination below triple-A is 15%. Holding the quality of the underlying loans fixed, higher subordination implies the deal is rated more conservatively, because the fraction of highly-rated bonds is smaller.

The first part of our analysis studies the determinants of subordination, and time-series trends in rating standards. We first document that average unconditional subprime subordination levels *increase* between 2001 and the end of 2004, and then are relatively flat until mid-2007. A similar pattern, albeit less pronounced, is evident for Alt-A deals.

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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). In similar vein, Devan Sharma, President of S&P, writes: "*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).

Estimating a simple model of ratings determination, we show that subordination is related in the expected directions to fundamentals like the level of mortgage credit risk (based on a simple "ex-ante" default model), and the strength of credit enhancement features in the deal. Controlling for these factors, we find a hump-shaped pattern in initial subordination between 2001-07. Namely, risk-adjusted subordination increases between 2001 and 2004, but then declines significantly between the start of 2005 and mid-2007. During this latter period, the average riskiness of new MBS deals increases significantly, based either on our default model, or on other metrics such as early-payment defaults, house price appreciation, and mortgage underwriting characteristics. However, the fraction of highly-rated MBS in each deal remains flat, rather than increasing in response to this greater risk. Consistent with this ex-ante evidence, these later vintages, particularly 2006 and 2007, also perform worst ex-post, and are downgraded most heavily, as shown in Figure 1.

The second part of our analysis examines how well credit ratings order *relative* risks across MBS deals from within a given cohort. Here we focus on studying variation in realized performance. If credit ratings are informative, mortgages underlying deals rated more optimistically (i.e. lower subordination, or equivalently a larger fraction of highly-rated securities), should perform better ex-post, in terms of lower mortgage default and loss rates. Furthermore, prior information available when the deal was initially rated should not be expected to systematically predict deal performance, after controlling for credit ratings. This is because this prior information should *already* be reflected in the ratings themselves, to the extent it is informative about default risk.

We find higher subordination is generally correlated with worse ex-post mortgage performance, as expected. However, conditional on subordination, time dummies and credit enhancement features, we also find significant variation in performance across different types of deals. First, MBS deals backed by loans with *observably* risky characteristics such as low FICO scores and high leverage (summarized by the projected default rate from our simple ex-ante model) perform poorly relative to initial subordination levels. Moreover, deals with a high share of low- and no-documentation loans ("low doc"), perform disproportionately poorly, even relative to other types of observably risky deals. This suggests such deals were not rated conservatively enough ex-ante.

These findings hold robustly across several different measures of deal performance: (i) early-payment defaults; (ii) rating downgrades; (iii) cumulative losses; (iv) cumulative defaults. In some cases, our results are magnified for deals issued during the period of peak MBS issuance from the start of 2005 to mid-2007. However, perhaps most notably, we repeat our analysis separately for each annual deal cohort between 2001 and 2007. We find that the underperformance of low-doc and observably high risk deals holds surprisingly robustly over the entire sample period, including earlier deal vintages not significantly affected by the crisis. Indeed, these differences in performance can be observed even only based on performance data publicly available before the crisis starts.

While our results are not conclusive about the role of explicit incentive problems, two findings appear consistent with recent theoretical literature that models these frictions. First, Mathis, McAndrews and Rochet (2009) and Bolton, Freixas and Shapiro (2009) predict rating standards will decline when security issuance volume and revenues are high relative to reputational costs of errors. This appears consistent with our finding that risk-adjusted subordination declines between early 2005 and mid-2007, which we show coincides with the peak of MBS deal volume.

Second, Skreta and Veldkamp (2009) and Sangiorgi, Sokobin and Spatt (2009) predict rating inflation should generally be increasing in security "opacity" or "complexity" (defined as residual uncertainty about security value). We argue the share of low-doc loans underlying the deal is a reasonable proxy for opacity for our sample, since evaluating the quality of such loans relies on "soft" self-reported information from the borrower about their income, rather than verifiable data like tax returns. Our finding that "low-doc" deals underperform relative to their ratings, even by comparison to other types of risky deals, thus appears consistent with this "opacity" prediction.

This paper presents the first comprehensive academic analysis of residential MBS ratings in the period leading up to the crisis. Since related research has shown credit ratings significantly influence security prices (Adelino, 2009; Kisgen and Strahan, 2009; Chernenko and Sunderam, 2009), apparent rating misalignments identified in our analysis are likely to have significantly influenced the cost of subprime credit, particularly for low-doc mortgages and loans with observably poor underwriting characteristics. High MBS ratings also fed the market for collateralized debt obligations (CDOs), since CDO subordination levels were directly based on the ratings of the individual mezzanine mortgage bonds that made up the deal.

Our findings relate to an active policy debate about regulation of the credit rating industry.[3] To assess the need for industry reform, it is necessary to have reliable evidence about past rating performance. Our evidence suggests MBS ratings are informative, and rejects a simple story that ratings continuously deteriorate from 2001-07. However, it also identifies shortcomings in ratings, particularly during the market peak in 2005-07, when incentives to produce favorable rating opinions were arguably strongest. This suggests regulation of rating agencies should be particularly alert to credit booms such as the one recently observed in the subprime market.

1. Institutional Background

This section provides a short introduction to non-agency mortgage securitization. For more details, interested readers are referred to Gorton (2008) and Ashcraft and Schuermann (2008).

1.1 Background on non-agency MBS deals

The term "non-agency" refers to MBS deals without a credit guarantee from Ginnie Mae, Fannie Mae or Freddie Mac. The structure of a typical non-agency deal is shown in Figure 2. Individual mortgages are combined into one or more pools and held in a bankruptcy-remote trust. A set of bonds are then issued with different claims to the cashflows from the loans in the trust.

[3] Mathis et al. (2009) propose a "platform pays" model, where a central platform decides who rates each deal, removing the ability of issuers to "shop" across CRAs. See Richardson and White (2009) for a related proposal. Consistent with the spirit of these proposals, on May 13, 2010, the U.S. Senate passed a bill requiring the creation of a rating board overseen by the SEC that select which CRAs rate future structured finance deals.

Because of the lack of a credit guarantee, non-agency MBS investors are exposed to credit risk due to borrower defaults that lead to realized losses (e.g. a foreclosure sale whose net proceeds are less than the mortgage face value). Deals are structured with *credit enhancement* features to protect investors from credit losses. These include the following:

Subordination. As shown in Figure 2, non-agency MBS deals have a "senior-subordinated" structure, where mortgage principal payments are first paid to senior tranches, while realized mortgage losses are first applied to the junior claims. The most junior class is referred to as the equity tranche. This 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. Senior securities generally have the highest credit ratings, and since they are last in line to absorb credit losses, pay the lowest yields to investors.

Excess spread. As additional credit support, the interest payments from the mortgage loans underlying the deal will typically exceed the sum of servicer fees, net payments to the interest rate swap counterparty, and coupon payments to MBS issued by the trust. This difference, referred to as excess spread, is used to absorb mortgage credit losses, with any remainder either kept in reserve or distributed each month to the owners of the equity tranche. Excess spread is particularly important for junior tranches, which are first to absorb losses, compared to senior tranches which are also protected by a larger subordination buffer.

Insurance. Some tranches in some deals are insured or "wrapped" by an external bond insurer, who promises to compensate investors for any principal losses on the bond. Insured tranches are generally assigned the credit rating of the insurer, which inevitably exceeds the natural rating of the bond in the absence of insurance. Thus, such deals will have lower subordination, all else equal.

Other. Credit enhancement for each bond is also affected by performance triggers (which govern how cashflows are split amongst different security types depending on mortgage pool performance), the structure of interest swaps used, and other features of the pooling and servicing agreement. See Ashcraft and Schuermann (2008) for more details.

1.2 Primer on credit ratings

A credit rating is an opinion of the credit risk of a fixed income security, summarized as a discrete alphanumeric grade (e.g. triple-A).[4,5] The rating reflects the likelihood of a lifetime default on the security, and is periodically revised over the bond's life. Our focus in this paper is on evaluating the *initial* ratings assigned to MBS when issued, since these are most relevant for initial pricing of the securities in the deal and thus for the supply of mortgage finance.

Credit ratings for an MBS deal are normally summarized in terms of the level of *subordination* below a given letter rating. In our analysis we calculate subordination as follows:

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

For example, subordination below BBB- of 5% means 95% of the bonds in the deal receive a rating of BBB- or higher. The 5% subordinate class of claims may include both traded securities with a rating below BBB-, or the unrated equity tranche. Note that, although the rating on each bond takes a discrete letter value, subordination is a *continuous* variable between 0% and 100%. Deals backed by riskier mortgages should have more subordination below any given letter rating, because the distribution of potential mortgage credit losses is shifted to the right.

While ratings represent a relative, rather than absolute, measure of credit risk, CRAs state that a given rating should in principle have a consistent interpretation through time and across different security types. For example, Moody's (1999) states that *"while it is impossible to produce*

[4] CRAs differ somewhat about what exactly is assessed. Ratings from Standard and Poor's (S&P) can best be thought of as a measure of the probability of default. e.g. S&P (2007a, p. 3) states that: "*[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*." By contrast, Moody's and Fitch incorporate estimates of expected bond recovery rates, and thus can better be thought of as a measure of expected loss (e.g. Moody's, 2008).

[5] MBS ratings use the same scale as corporate bond ratings. Including modifiers, ratings by S&P, Fitch and DBRS fall on a 22-notch scale (AAA to D), while Moody's ratings fall on a 21-notch scale (Aaa to C).

constant <u>*realized*</u> *default rates, one of Moody's goals is to achieve stable* <u>*expected*</u> *default rates across rating categories and time",* Standard and Poor's (2007a, p.4) states that "*[o]ur ratings represent a uniform measure of credit quality globally and across all types of debt instruments.",* and Moody's (2004) states *"[t]he comparability of these opinions holds regardless of the country of the issuer, is industry, asset class, or type of fixed-income debt."*

Against this goal, CRAs also emphasize their belief that investors desire a degree of rating *stability* in response to macroeconomic shocks. For this reason, ratings are revised only gradually in response to changes in economic conditions, a practice known as "rating through the cycle". (Moody's, 1999; Altman and Rikjen, 2005; Amato and Furfine, 2004; Lofler, 2004). Cantor (2001), representing Moody's, writes: *"Moody's analysts attempt to balance the market's need for timely updates on issuer risk profiles, with its conflicting expectation for stable ratings*". Empirically, Amato and Furfine (2004) find corporate bond ratings do move unconditionally with the business cycle, but this is no longer true after conditioning on changes in business and financial risks.

Since we focus on the quality of *initial* MBS ratings, our analysis does not speak to whether ratings on seasoned securities are revised slowly in response to shocks. Our analysis does point to significant time-series variation in risk-adjusted initial subordination levels. We discuss in Section 6 whether these trends can easily be reconciled with the "rating through the cycle" principle.

1.3 Rating process for non-agency MBS deals

The MBS rating process involves a combination of formal statistical modeling and subjective judgment. In terms of statistical analysis, CRAs maintain econometric prepayment and default models, which use as inputs macroeconomic variables, particularly home prices and interest rates, as well as loan characteristics. The CRA simulates paths of these macroeconomic variables, which are substituted into their econometric models to calculate a path of defaults and losses. These loss projections are then aggregated across paths to produce a distribution of losses. This distribution is used to set subordination levels below each rating class, after taking into account credit enhancement features such as excess spread. See Moody's (2008) and S&P (2007b) for more details.

Each agency's rating methodology and models evolve over our sample period, and involve a number of key areas where judgment must be applied. These include the structure of the models used, and decisions about the distribution of home price changes and other macroeconomic variables. Home price forecasts used by CRAs are generally anchored by current data (e.g. in Moody's ratings model, house price growth is based on interest rates and two lags of past home price growth; see Moody's, 2008). Specific ratings for each MBS deal also incorporate further subjective assessments of the quality of mortgage originators and servicers, and assessments of data integrity and representations and warranties, and other judgmental adjustments[6].

2. Literature review

A number of recent theoretical papers model incentive problems in the credit rating process. Bolton et al. (2008) assume each CRA has a private signal of the quality of a security to be rated, which can be either reported truthfully or misreported. Misreporting leads to an exogenous reputation cost if detected, but generates higher fee income from security issuers in the current period. Bolton et al show ratings inflation is more severe when reputation costs are low relative to current rating profits, suggesting CRAs are more likely to misreport risk during booms.

Mathis et al. (2009) explore reputation further in a dynamic game where CRAs switch between an "honest" type that must always report their private signal truthfully, and a dishonest CRA that can choose to give an incorrect report. When the share of income from rating complex products is high enough, the CRA of dishonest type is always too lax with positive probability. For some parameters, equilibrium with "reputation cycles" in rating standards is possible. Bar-Isaac and

[6] Illustrating this flexibility and subjectivity, an Standard and Poor's internal email reported in US Senate (2010, p. 127), states: *"It might be too much of a stretch to say that we're complying with it* [with published rating methodologies] *because our SF rating approach is inherently flexible and subjective, while much of our written criteria is detailed and prescriptive".*

Shapiro (2010) present a related dynamic model which predicts ratings are less accurate during booms because of greater labor market competition for rating analysts.

Skreta and Veldkamp (2009) study the relationship between rating bias and asset *complexity,* modeled as the level of uncertainty about true security value. While rating bias is minimized when complexity is either very low or very high, in calibrations, rating shopping and rating inflation is generally increasing in complexity. Sangiorgi et al. (2009) derive a similar result, that rating bias and selection effects are increasing in "opacity", defined as the degree of heterogeneity in signals about security value. Related work on incentive problems includes Mariano (2008), Opp and Opp (2009), Faure-Grimaud, Peyrache and Quesada (2007), and Boot, Milbourn and Schmeits (2006).

2.1 Related empirical work

Most empirical work on ratings focuses on corporate bonds. This research demonstrates ratings tend to be revised slowly to new information, and are relatively invariant to the state of the business cycle, consistent with the "rating through the cycle" principle (Amato and Furfine, 2004). While Blume, Lim and McKinley (1998) argue corporate bond ratings have become more conservative over time, Amato and Furfine (2004) argue this finding largely disappears after controlling appropriately for firm-level measures of risk. More recently, Becker and Milbourn (2010) find evidence that the market entry of Fitch reduces the quality of corporate bond ratings.

Turning to structured finance ratings, Benmelech and Dlugosz (2010) document the wave of recent downgrades across different types of collateralized debt obligations (CDOs). They find evidence that securities rated by only one CRA are downgraded more frequently, which is interpreted as evidence of rating shopping. Griffin and Tang (2009) find that published CDO ratings by a CRA are less accurate than the direct output of that CRA's internal model, suggesting judgmental adjustments were applied to model-generated ratings that worsened rating quality. . Coval, Jurek and Stafford (2009) show default probabilities for structured finance bonds are very sensitive to correlation assumptions. Studying MBS, He, Qian and Strahan (2009) present evidence that large security issuers receive more generous ratings, particularly for securities issued from 2004-06. (Unlike this paper, however, these authors are not able to control for information on deal structure or underlying mortgage collateral). Cohen (2010) finds evidence that measures of rating shopping incentives, such as the market share of each CRA, affects commercial MBS subordination

Most similar to this paper in terms of data, Nadauld and Sherlund (2009) analyze interactions between home prices, MBS demand and primary market credit supply, also using a matched dataset of mortgages and MBS for a sample of 1,267 subprime deals. While credit ratings are not their main focus, Nadauld and Sherlund do find that MBS deals backed by loans in areas with high home price appreciation receive more generous ratings, a result we replicate.

Finally, a number of papers present evidence that credit ratings matter for bond prices and the supply of credit. Kliger and Sarig (2000) study Moody's introduction of rating modifiers (e.g. single-A is split into A1, A2 or A3). Information revealed by this refinement is shown to shift prices of bonds which previously had the same rating. Kisgen and Strahan (2009) present evidence that ratings influence prices through their role in financial regulation. They show the certification of DBRS by the SEC shifts prices in the direction of their DBRS rating amongst bonds *already* rated by DBRS. Adelino (2009) finds performance of junior triple-A MBS bonds is uncorrelated with initial prices, suggesting triple-A investors relied excessively on credit ratings, rather than conducting due diligence. Chernenko and Sunderam (2009) find ratings variation around the investment grade boundary creates market segmentation that affects credit supply and firm investment.

3. Data and stylized facts

Our analysis is based on a sample of 3,144 subprime and Alt-A MBS deals issued between 2001 and 2007. This sample is constructed by matching security-level information from Bloomberg and ABSNet and loan-level data from LoanPerformance (LP), and aggregating to the deal level.

A detailed explanation of how our dataset is constructed is provided in Appendix B. From Bloomberg and ABSNet we collect data on the characteristics of each security at issuance, including face value, coupon rate and seniority, as well initial credit ratings and any revisions from Moody's, S&P, Fitch and DBRS. From LP we extract data on the characteristics of each mortgage in every deal, such as amount, origination date, borrower credit ("FICO") score, loan-to-valuation (LTV) ratio, property ZIP code and so on. We also extract data on loan status at different horizons after the deal was issued (e.g. prepaid, current, 30 days delinquent, in foreclosure etc.). We then match security and loan-level data together using a concordance provided by LP. We classify deals as subprime or Alt-A based on their assignment in LP, and analyze these two deal types separately. For comparability reasons, we exclude deals backed by negative amortization loans.

Figure 3 plots nonprime MBS issuance for our sample, and for the industry as a whole as reported by the mortgage industry newsletter Inside Mortgage Finance. Comparing the two totals demonstrates that our data represents a high fraction of total nonprime securitization volume over this period. (Coverage is somewhat lower in the Alt-A segment, because we drop negative amortization deals, which are nearly always classified as Alt-A in LP.) This figure also highlights the striking growth and subsequent collapse of MBS securitization volume over this period. Issuance peaks between late 2004 and mid 2007, when around 250 new deals are issued each quarter. This declines rapidly in the second half of 2007, and drops to zero by 2008.

3.1 Measuring credit enhancement

In line with industry practice, we summarize credit ratings for each deal via levels of *subordination*. This is simply the complement of the fraction of highly-rated securities in the deal. (e.g. If 85% of the deal receives a triple-A rating, then triple-A subordination is 15%). In our empirical work we focus on subordination at two points: below triple-A, and below the investment grade boundary (BBB-). For deals rated by multiple CRAs, we calculate subordination based on the most conservative rating, although especially at the triple-A boundary, rating disagreement amongst CRAs is limited. When calculating subordination levels we take care to avoid double counting of mortgage strips and exchangeable tranches (see Appendix B for details.)

We also construct variables measuring different types of credit enhancement, and a proxy for the correlation of mortgage losses. Mortgage defaults and losses are correlated because of common shocks to home prices and economic conditions. Since these shocks have a strong spatial component, especially for home prices, our analysis controls for a simple measure of geographic concentration, namely the sum of the squared value-weighted share of mortgages from each US state. Geographically concentrated deals will have a wider joint distribution of losses, all else equal, because they are less diversified against local housing and economic shocks.

To identify external credit enhancement, we record whether the deal has external bond insurance, and insurance face value as a fraction of deal size. We also calculate 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, which, as discussed in Section 1, provides additional credit protection to MBS bondholders.

3.2 Stylized facts

Table 1 presents summary statistics for the deals in our sample. The average deal is backed by $749m in loans. Alt-A deals are backed by higher-quality mortgages than subprime deals on average, and correspondingly have lower subordination levels (93.1% of an average Alt-A deal receives a triple-A rating, compared to 82.4% for an average subprime deal). These averages match closely with subordination levels reported in other sources (e.g. US Senate, 2010; Ashcraft and Schuermann, 2008; Gorton, 2008). Table 1 also shows that nearly every deal is rated by either two or three CRAs amongst Moody's, S&P, Fitch and DBRS. Moody's and S&P are dominant within this group.

Table 2 presents summary statistics for the mortgages underlying these deals. There are significantly more loans on average in subprime deals than Alt-A deals, in part reflecting greater concentrations of junior-lien mortgages. Consistent with conventional wisdom, mortgages in Alt-A deals have higher FICO scores and lower LTV ratios, but are more likely to be interest-only or involve low or no documentation of borrower income and assets.

Table 3 presents time-series trends in several key variables. Notably, the fraction of interest only and low- or no-documentation loans increases significantly over the sample period, while the fraction of deals supported by external bond insurance declines over time.

3.3 Trends in credit enhancement

Figure 4 plots time-series trends in subordination at different attachment points. The two vertical lines represent the approximate period of peak MBS issuance (Q1:2005 to Q2:2007).

Notably, subordination increases in the first part of the sample, from 2001 to the end of 2004, particularly amongst subprime deals. This implies ratings become more conservative over this period, at least unconditionally. While this stylized fact may appear surprising, it is consistent with trends in subordination cited by CRAs themselves (e.g. Kanef, 2007, reports a 30% increase in Moody's subordination levels over a similar period). Between early 2005 and mid 2007, observed subprime subordination levels are fairly stable, while Alt-A subordination declines slightly. Finally, subordination increases sharply, especially for subprime deals, in the last two quarters of our sample, after the onset of the crisis. In the next part of our analysis we revisit these trends after conditioning subordination on changes in mortgage risk and credit enhancement.

4. Loan-level model

In this section we estimate a simple loan-level mortgage default model. This model is used to compute an average predicted mortgage default rate for each MBS deal. These projections are used later in our analysis of credit ratings. Importantly, this projected default rate is intended to be an ex-ante measure of risk, constructed *only* using information available to CRAs at the time each deal was initially rated and issued. This is done by estimating the model recursively over different subsamples, as described below.

The default model is a logit regression based on a random 10% LoanPerformance (LP) sample (Note: LP coverage begins in April 1992). LP mortgage data is merged with FHFA house price data at the state or MSA level (depending on whether the mortgage property is located inside an MSA), and the state unemployment rate. Our main steps are as follows:

1. We split the sample of MBS deals into 14 six-month subsamples by issuance cohort or vintage (first half 2001, second half 2001, and so on, up to second half 2007).
2. We estimate the loan-level default model 14 times, using data from 1992 up to three months prior to the start of each cohort[7]. (We reserve one quarter to account for data release lags.)
3. For every MBS deal in our sample, we substitute the characteristics of each mortgage in the deal into the corresponding default model, and compute a predicted default probability (e.g. each mortgage from any deal issued between January-June 2006 would be plugged into the default model estimated using data up to September 2005).
4. Averaging the default probabilities from step three, we calculate a weighted average mortgage default rate for each *deal*, weighting by mortgage principal at of issuance date.

The dependent variable is set equal to one if the mortgage is 90+ days delinquent, real-estate owned (REO) or prepaid with loss 12 months after origination, and zero otherwise. Explanatory variables include mortgage characteristics at origination like the borrower FICO score, combined LTV, debt-payments-to-income (DTI), dummies for income and asset documentation (full-, partial- and low-doc), and so on. We also control for the state unemployment rate at the time of loan origination, and recent trailing house price appreciation, measured by the 12-month ended trailing percentage FHFA home price growth rate. We also include time dummies at six-monthly intervals, to reflect any time-series trends in mortgage default rates not captured by the model variables.

[7] e.g. We first estimate the model using data from April 1992 to September 2000, three months prior to our first cohort which covers MBS deals issued between January and June 2001. Then we re-estimate the model updating the sample end date to March 2001, then to September 2001, and so on, up to March 2007.

Table 4 presents logit estimates for the model estimated over our entire sample period. These results are consistent with expectations, and with other studies of the determinants of mortgage default over this period (e.g. Demyanyk and Van Hemert, 2009, Haughwout, Peach and Tracy, 2008, and Bhardwaj and Sengupta, 2009). Note that *past* home price appreciation is significantly negatively correlated with *future* mortgage default rates, reflecting the high autocorrelation in house price growth (Case and Shiller, 1987).

Figure 5 plots the average model-projected 12-month serious delinquency rate by deal vintage. Notably, predicted default rises sharply in 2006 and 2007, implying that deals from these vintages were significantly riskier than earlier cohorts. Also plotted on this figure is the ex-post *realized* 12-month serious delinquency rate for mortgages from each vintage. Predicted and realized default rates do co-move quite closely, although the model significantly under-predicts realized default rates at the end of the sample. Since the model is purely backward looking, this seems unsurprising given the unexpectedly sharp deterioration in the US housing market and credit conditions observed during the period leading up to the financial crisis. Gerardi et al. (2008) show that ex-ante models, such as ours, perform reasonably well in accounting for the rise in defaults if one plugs in the *realized* ex-post path of house prices. However, this is a different thought experiment to ours, since of course, this ex-post home price realization was not known when the deal was originally issued and rated.

While we are careful to estimate the model parameters only using prior available data, a "look-back" bias may also arise if our choice of explanatory variables or model structure is influenced by knowledge of the evolution of the crisis. To minimize these concerns, we deliberately choose a simple model structure (a basic logit), and consider only explanatory variables that CRAs also used in the rating process. For example, Moody's (2003) description of their primary subprime ratings model lists as inputs all the main variables included in our default model specification.[8]

We emphasize that this default model is intentionally simple, to avoid look-back biases, and in several respects is less complex than the models used by rating agencies themselves.[9] Any shortcomings of our model *lower* the benchmark against which credit ratings are compared as a predictor of deal performance (see Section 7 for further discussion).

5. Empirical predictions

The goal of our empirical analysis is simply to assess how well credit ratings summarize cross-sectional and time-series variation in default risk to bond investors across the 3,144 MBS deals in our sample. This section describes our main hypotheses in more detail.

The first part of our analysis studies the ex-ante determinants of MBS ratings. We investigate whether ratings are related to fundamentals in the expected directions: namely, whether subordination is increasing in mortgage credit risk, and decreasing in geographic diversification and the strength of credit enhancement features such as bond insurance and excess spread. We then study time-series trends in subordination levels conditional on these fundamentals. Our approach is related to Blume, Lim and MacKinlay (1998), who study time-series trends in corporate bond ratings.

Our null hypothesis is that subordination levels are stable through time, after controlling for changes in risk. This benchmark is motivated by statements from CRAs that rating opinions should ideally have a consistent interpretation regardless of the time they are issued (see Section 2 for

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[8] Moody's (2003) lists the following variables as inputs into their Moody's Mortgage Metrics ratings model: FICO, DTI, LTV, loan purpose, property type, interest rate, interest rate adjustment type (fixed versus adjustable, balloon), owner occupancy status, documentation level, home value, and the presence of mortgage insurance. Standard and Poor's LEVELS model is based on a similar set of inputs, also including all the main variables employed in our default model (e.g. see S&P, 2007b).

[9] Based on public documents, CRAs use simulations to estimate an explicit distribution of cashflow losses, using time-series models of the term structure and house prices CRAs also conduct due diligence on the issuer and originators, make use of additional underwriting variables not included by us, and account for risk layering (i.e. interaction effects between risk variables). See Moody's (2003, 2007, 2008) and S&P (2007b) for details.

further discussion). One alternative hypothesis, consistent with Mathis et al. (2009) and several other papers, is that ratings are inflated during boom periods of high security issuance.

Hypothesis 1 (Rating stability): *The fraction of subordination remains stable through time, after controlling for the level of mortgage credit risk and the strength of credit enhancement.*

The second part of our analysis studies variation in ex-post deal performance, measured by mortgage default rates, realized losses, and also credit rating downgrades. We focus on relative performance across deals *within* a given vintage, by including year x quarter fixed effects in our analysis. This strips out time-series variation in performance due to purely aggregate shocks.

If subordination levels appropriately reflect the relative credit risk of the mortgages underlying each deal, then mortgage performance (defaults and realized losses) should align well with initial subordination levels: that is, deals with lower subordination should experience lower mortgage default and loss rates ex-post. Furthermore, prior data, such as the model-projected default rate constructed in Section 4, should not be expected to systematically predict relative deal performance, controlling for subordination. This is because any relevant information from this data should already be reflected in the ratings themselves, since it was part of the CRAs information set.

Hypothesis 2 (Risk ranking)*: (i) Within a vintage, subordination levels are positively correlated with ex-post mortgage default and loss rates; (ii) Controlling for initial subordination, ex-ante data available to CRAs does not systematically predict mortgage performance or rating downgrades.*

We also test a more specific hypothesis of Skreta and Veldkamp (2009) and Sangiorgi et al. (2008) that rating bias should be greater for complex or opaque securities. We consider the concentration of low-documentation ("low-doc") mortgages as a good proxy for complexity or opacity within our sample. Full documentation borrowers provide hard documentary evidence of income and assets, including tax returns, paystubs, and financial statements. For low-doc loans, a

CRA or investor must rely on soft information, namely the borrower's self-report. There is thus substantial uncertainty about whether this report is accurate, especially given the distance between the CRA or investor and the point of loan origination.[10] Thus, as a test of the hypothesis, we test whether MBS deals with a high fraction of low-doc loans perform *relatively* worse ex-post, conditional on subordination levels, than other types of deals. The null hypothesis is that ratings appropriately reflect the additional risk associated with these loans:

Hypothesis 3 (Opacity): *Deals with a high fraction of low-documentation mortgages do not systematically underperform other deals, controlling for initial subordination levels.*

While our analysis of ex-post performance focuses only on within-cohort variation, our results may still be unduly influenced by the specific types of shocks associated with the housing market collapse and onset of the financial crisis in 2007-08. As a sensitivity test, in addition to pooled regressions, we also analyze MBS deal performance separately cohort-by-cohort for each vintage between 2001 and 2007, focusing on early-payment defaults. This cohort analysis includes earlier vintages of MBS deals that performed well on average, and were not significantly affected by the crisis. As described in Section 7, our main empirical findings are actually strikingly consistent, despite large differences in realized performance across cohorts.

6. Determinants of subordination

In this section we estimate a simple regression model that relates MBS subordination to proxies for the level of credit risk facing bond investors. The specification is:

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[10] Low-doc mortgages are designed to assist borrowers who for various reasons are unable or unwilling to document genuine income that could contribute to mortgage payments (e.g. anticipated future bonuses or business income, or cash income not reported for tax purposes). Some borrowers also select low-doc loans to reduce paperwork and expedite the loan approval process. As well as these "benign" explanations, however, low-doc borrowers may also have incentives to exaggerate income and assets to qualify for more credit or a lower interest rate. Harney (2006) reviews survey data from mortgage brokers, reporting that low-doc loans were often used to exaggerate income or conceal the fact that reported income is earned by a household member with poor credit. Jiang, Nelson and Vytlacil (2009) and Rajan, Seru and Vig (2008) also analyze the performance of low-doc mortgages, although these papers do not study credit ratings, the focus of our paper.

AAA subordination = f(mortgage credit risk, credit enhancement, diversification, time dummies) **[1]**

As discussed, subordination below AAA is simply the fraction of the MBS deal that does not attract a triple-A rating. Higher subordination indicates that the deal is rated more conservatively, other things equal.[11]

The regression model relates subordination to the credit risk of the mortgages underlying the deal, the strength of credit enhancement features that provide additional support to bondholders, including insurance and excess spread, and a measure of the geographic diversification of the mortgage collateral. A geographically diverse pool should achieve lower subordination, because diversification reduces the variance of the *joint* distribution of mortgage losses, which is what is relevant to bond investors. We also include year x quarter dummies, which will capture any time-series changes in ratings controlling for our measures of risk.

Table 5 presents empirical estimates, which are estimated separately for subprime deals (Columns 1 and 2) and Alt-A deals (Columns 3 and 4). The dependent variable in each specification is ln(1+percent subordination below AAA). Subordination is specified in logs so that the time dummies shift subordination proportionately to each deal's baseline risk level. The model is estimated using least squares, with standard errors clustered by year x quarter.

The projected default rate developed in Section 4 is used as the primary summary statistic of mortgage credit risk. To account for non-linearities, two transformations of this variable are included, the natural log, and its square. As expected, subordination is strongly positively and statistically significantly related to this measure of mortgage default risk. As additional controls for mortgage quality, Columns 2 and 4 also control for six weighted mortgage summary statistics for the deal, constructed using LoanPerformance data: average FICO, CLTV, trailing HPA, and the value-

[11] In unreported regressions, we re-estimate equation [1] using subordination below investment grade (BBB-), and below single-A, instead of AAA. Results are similar, in terms of the sign and statistical significance of subordination determinants and trends in risk-adjusted subordination. R^2 is lower for the BBB- subordination regression, which we think reflects that this attachment point is measured with relatively more noise.

weighted fraction of low-doc, investor and interest-only mortgages. These controls account for any differences between the weights placed on each mortgage risk covariate in the rating process relative to its coefficient in the loan-level default model. As the table shows, the other estimated coefficients are robust to the addition of these additional controls. The aggregated loan-level variables themselves are jointly significant for Alt-A deals but not subprime deals.

To measure external credit enhancement, we include a dummy for whether any part of the deal is insured by a third party bond insurer, and a continuous variable measuring the fraction of the deal that is insured. For subprime deals, where external bond insurance is more common, both these variables are negatively signed and statistically significant, consistent with expectations[12]. To control for excess spread at origination, the specification includes the average mortgage coupon rate and the average bond coupon rate. Excess spread reflects the difference between these two variables.[13] We also include a proxy for geographic mortgage concentration, namely Σ_i (*fraction of mortgage balances from state i*)^2. This variable takes values between 0.02 (equal mortgage balances from each state) and 1 (all loans from one state). As predicted, more concentrated deals have higher subordination, reflecting their greater exposure to state-specific shocks. Examining the regression R^2's, these explanatory variables explain over half the variation in subordination levels for subprime deals, although significantly less, around 20-30 percent, for Alt-A deals. The lower explanatory power for Alt-A may be accounted for by the more opaque collateral underlying these deals.

The coefficients on the year x quarter dummies trace out residual changes in subordination unexplained by the risk and credit enhancement variables in Table 5. The time paths of these dummies, and their standard error bands, are plotted in the two left-hand panels of Figure 6, labeled

[12] Since wrapped deals may be different on other unobservable dimensions to the rest of our sample, we also re-estimate Table 5 and 6 of this paper after dropping these deals from our sample, as a robustness check. Our results are similar to those shown (results available on request).

[13] We include the two measures separately, rather than just the difference, because the mortgage coupon rate may also be a proxy for the credit risk of the mortgages in the deal. Consistent with this interpretation, subordination is generally positively correlated with the average mortgage interest rate.

as “risk-adjusted subordination”. Also plotted is the path of unconditional triple-A subordination from Figure 4. We normalize conditional and unconditional subordination to be equal in 2004:Q4.

The figure documents significant variation in risk-adjusted credit ratings over the sample. Subordination increases significantly between the Q1:2001 and the end of 2004, not just unconditionally, but also after controlling for deal characteristics. While unconditional subordination remains approximately constant from the start of 2005 until the end of the securitization boom in mid-2007, *risk-adjusted* subordination declines significantly over this period. Quantitatively, between Q1:2005 and Q2: 2007, subordination declines by 13 percentage points for subprime deals, and 3 percentage points for Alt-A deals, around half of the sample average for both deal types.

Even without estimating a regression, this observed shift in rating standards can be seen simply by comparing Figures 4 and 5. Figure 4 shows that projected default from the loan-level model increases sharply in 2006 and 2007, implying that MBS deals constructed from these loans became progressively riskier over this period. However, subordination levels remain flat or even decline slightly (Figure 5), suggesting MBS ratings did not respond appropriately this increase in risk. As Table 5 shows, a statistical test for whether average subordination declines during the “credit boom” period between Q1:2005 and Q2:2007 rejects the null hypothesis of stability at the 1% level in Columns 1, 2 and 3, and at the 4% level in Column 4.

The right-hand panels of Figure 6 decompose the cumulative change in risk-adjusted subordination after 2004 into four components: (i) changes in unconditional subordination, (ii) changes in house price appreciation, (iii) changes in other components of mortgage credit risk, (iv) changes in credit enhancement and geographic diversification.[14] US house price appreciation peaks at the end of 2005, and falls sharply thereafter. This declining HPA accounts for about half the

[14] The contribution of HPA is calculated by recomputing the projected default rate for each post-2004 deal after setting trailing house price appreciation in each zip code equal to its 2004:Q4 level, rather than its actual value in the issuance quarter. Using the deal-level specification from Table 5, we then calculate the difference between predicted subordination under the usual model default rate and this alternative measure that excludes home price changes. The contribution of other deal characteristics is calculated in a similar way, except that we simply replace the model default rate in each subsequent quarter with its average 2004:Q4 value.

observed decline in risk-adjusted subordination. The contribution of "other mortgage characteristics" accounts for other determinants of the rising model-projected default rate after 2004, namely changes in average loan covariates (e.g. LTV, FICO scores), and changes in the estimated model coefficients. These factors significantly contribute to rising mortgage risk over this period, as also documented by Demyanyk and Van Hemert (2009). Changes in geographic diversification and the strength of credit enhancement make only a small contribution to changes in risk-adjusted subordination.

6.1 Discussion

The above results suggest risk-adjusted subordination levels vary significantly through time, and decline significantly at the tail of the mortgage credit boom. While our quantitative estimates are potentially sensitive to our modeling approach, we believe the finding that risk-adjusted subordination falls between the start of 2005 and mid-2007 is likely to be robust to a broad range of specification changes. Several types of ex-ante or "real-time" evidence suggested risk was progressively increasing during this period: (i) early payment defaults by cohort were progressively rising (Figure 5, and Demyanyk and Van Hemert, 2009); (ii) HPA declines beginning in late 2005, (iii) the predicted 12-month default rate from the "ex-ante" model in Section 4 increases significantly and persistently[15], and (iv) as documented in Table 3, most major loan underwriting characteristics generally deteriorate between 2004-07. Despite these indicators of rising risk, initial subordination levels stay flat during this period, or even decline slightly. Consistent with this ex-ante evidence of declining standards, MBS deals issued in 2006 and 2007 also experience the largest rating downgrades ex-post (Figure 1), and the largest price drops, measured by the Markit ABX.HE[16].

[15] We also experimented with estimating a more complex loan-level default model in which mortgage underwriting variables are interacted with each other and with time trends. Trends in predicted default are similar for this more complex model than for the benchmark model presented in Section 4.

[16] Each ABX.HE index tracks the price of a credit default swap linked to a reference basket of subprime MBS with a given original rating. As of 10/31/ 2009, the price of ABX.HE 2006-01 (linked to originally-AAA securities from deals issued in the second half of 2005) was 80.05% of par, but the 2007-01 and 2007-02 AAA prices (linked to MBS issued in the second half of 2006 and first half of 2007) were much lower, only 34% of par. See Stanton and Wallace (2009) for a detailed investigation of the informational content of the ABX.

Recent statements from some former CRA executives industry also seem consistent with our finding that subordination levels did not reflect rising risk after 2004 (Raiter, 2010; Cifuentes, 2010).[17]

One potential interpretation of these results is that CRAs take a "through the cycle" approach, ignoring or underweighting current home price trends when projecting future price growth. This is broadly consistent with ratings becoming more conservative from 2002 to 2005, as HPA increases, then less conservative in 2006 and 2007, as price growth slows. However, this cannot be a complete explanation, since the decomposition in Figure 6 shows that conditional subordination declines significantly between 2005 and 2007 even holding home price growth fixed. In addition, as discussed in Section 1, MBS ratings incorporate projections from autoregressive home price models, which are anchored by current price trends (see Section 1.3). This suggests CRAs place relatively less weight on the "through the cycle" principle when assigning structured finance ratings. This seems to make sense given that nonprime mortgages have a short expected life (2-3 years on average), relative to corporate bonds and corporate bond issuers.

A second possibility is that rating standards react with a sizeable lag to past mortgage performance. Early-payment defaults are relatively high for the 2001-02 vintages (Figure 5), which could account for the apparent increasing rating conservatism early in our sample. Early defaults are then low for deals issued in 2003-05, which may account for declining risk-adjusted ratings after this period. This lag in reacting to new information could be due to organizational inertia, for example.

A third interpretation is that shifts in rating standards reflect agency frictions. Bolton et al (2009), Mathis et al. (2009) and Bar-Isaac and Shapiro (2010) predict rating standards will decline

[17] Frank Raiter, former head of S&P's Residential Mortgage Rating Group, describes efforts to implement a new LEVELS rating model incorporating updated default histories and a larger loan sample. Adoption of the model was repeatedly delayed in 2004-05, and the model was never fully implemented. Raiter argues if the new model had been adopted *"the economics of deals incorporating the lowest quality subprime and Alt-A loans would have disappeared. In addition, the riskiest transactions submitted for ratings in 2005, 2006 and 2007 would likewise have been assigned much higher enhancement requirements which might have made it unprofitable for lenders to make additional loans"* (Raiter, 2010). Former Moody's executive Arturo Cifuentes testified to the same panel that CRAs *"failed to acknowledge the impact of the deteriorating standards in subprime lending, in spite of the fact that, as early as 2004, and clearly in 2005, there was enough evidence of fraud reported even in the mainstream media"* (Cifuentes, 2010).

during periods of high security issuance, since CRA incentives to misreport ratings are driven by a tradeoff between current revenues and future reputational costs. This could account for why risk-adjusted subordination declines between early 2005 and mid-2007, which our summary statistics demonstrate to be the period of peak MBS deal flow. It is less clear whether these models are consistent with our finding that subordination becomes more conservative from 2001-04, however.

7. Credit ratings and deal performance

The second part of our analysis studies the relationship between credit ratings and ex-post deal performance. Since most MBS deals in our sample are still active, and final losses on each bond are not yet determined, we examine several different *interim* measures of deal performance: (i) early-payment defaults such as the fraction of loans seriously delinquent after 12 months or at longer horizons, (ii) realized mortgage loss rates to date, and (iii) ex-post credit rating downgrades.[18] Each of these measures is closely analyzed by MBS market participants (e.g. ABX prices often move significantly upon release of remittance reports which provide updated default and loss data), suggesting they are useful indicators of deal performance. A comparison of our results across these different performance variables provides a robustness test of our results.

For each performance measure, we estimate variations of the following specification:

performance = f(subordination, model-projected default, share of low-doc loans, deal controls, other covariates, time dummies) **[2]**

'Subordination' is measured below both AAA and BBB-. Mortgage default and loss rates are expected to be increasing in subordination, since deals with greater risk should have been assigned a

[18] A different approach would be for us to examine variation in final realized principal losses on individual *securities* with the same initial rating. While we cannot yet do this, because these final losses have not yet been determined, we believe this would be an interesting exercise for future research.

smaller fraction of highly-rated securities. 'Deal controls' includes the same measures of credit enhancement and geographic concentration from Table 5.

Our null hypothesis is that subordination levels are calibrated to appropriately reflect available information about the credit risk of mortgages underlying the deal. Under this hypothesis, other ex-ante measures of the riskiness of the deal should not systematically predict deal performance, after controlling for initial subordination levels.

As risk benchmarks, we first consider the explanatory power for deal performance of the projected ex-ante mortgage default rate, which is an overall summary measure of mortgage risk based on observable loan characteristics (e.g. LTV, FICO scores etc.). We also separately study relative performance of deals with a high share of low-doc loans, which we view as a proxy for the opacity of the quality of the mortgage collateral, as well as other loan-level covariates: average LTV, FICO, trailing HPA, and the share of interest-only and investor loans. Each specification also includes year x quarter dummies, so that our analysis focuses only on relative deal performance *within* each vintage of deals, abstracting from aggregate shocks varying across vintages.

7.1 Early payment defaults

Table 6 studies the relationship between subordination and early payment defaults, defined as the weighted fraction of mortgages in default (defined as 90+ days delinquent, prepaid with loss or real-estate owned), one year after deal issuance. Juvenile defaults provide the earliest ex-post indicator of the quality of the underlying loans in an MBS deal. An additional advantage of this measure is that it is defined at a consistent horizon, since at least one year of delinquency data is available for each deal in our sample.

Higher subordination is generally statistically correlated with higher ex-post default rates, particularly for subprime deals. However, MBS deals backed by *observably* risky mortgages, as summarized by the model-projected default rate, consistently experience worse performance than would be predicted based on subordination levels. Comparing two deals with the same fraction of triple-A and investment-grade securities, a 10% increase in the projected mortgage default rate is associated with higher early payment defaults of 8% to 15%, statistically significant at the 1% level.

As can be seen from our model in Section 4, an MBS deal with a high share of low-doc loans will have a higher predicted default rate. However, strikingly, the low-doc share *independently* predicts worse performance, even conditional on the projected default rate. In other words, subordination levels are *disproportionately* too low for deals with a high "low-doc" share, compared to deals backed by loans that are risky on other dimensions (e.g. low FICO scores or high LTV). This result is statistically significant at the 1% level in each specification. (Notably, this finding only holds robustly for low-doc, signs on other loan-level covariates are mixed in columns 2, 3, 5 and 6).

Columns 3 and 6 interact the model-projected default rate and low-doc share with a 'credit boom' dummy, set equal to one between Q1:05 and Q2:07, the period of peak MBS deal flow. These interactions are positive and statistically significant for subprime deals, indicating the underperformance of these deal types is magnified around the market peak, and positive but insignificant for Alt-A deals.

Four specifications in Table 6 also include dummies for the number of CRAs (amongst Moody's, S&P, Fitch and DBRS) that rate part of the deal. Performance is unexpectedly poor amongst the few subprime deals rated by a single CRA. This replicates a finding of Benmelech and Dlugosz (2010), who study a broader range of structured finance bonds, and conduct analysis at the security rather than deal level.[19] We replicate this finding, even controlling for a wide range of deal and collateral characteristics not available to Benmelech and Dlugosz, albeit only for subprime deals.

7.2 Cohort regressions

Although the regressions in Table 6 include year x quarter dummies, it is still possible that our findings are influenced by shocks to relative performance associated with the financial crisis that

[19] While a significant fraction of securities are rated by one CRA, the senior tranches of more than 99% of the deals in our sample are rated by at least two CRAs. In other words, the share of deals rated soley by one CRA is very low, as shown in Table 2, even if some participating CRAs only rated part of the deal.

would have been difficult to predict ex-ante. To investigate this possibility, we re-estimate a more parsimonious version of this same regression cohort-by-cohort for each vintage between 2001 and 2007. Namely we regress the fraction of early-payment defaults on subordination below AAA and BBB-, the model-projected default rate, the fraction of low documentation loans, and the same set of deal controls used previously (insurance, excess spread, etc.). Results are presented in Table 7.

The main findings from Table 6 are strikingly robust across cohorts. Conditional on initial subordination levels, observably risky deals measured by the model-projected default rate, and deals with a high concentration of low-doc mortgages, experience higher early-payment defaults in every cohort, even amongst earlier cohorts issued during the housing boom whose early performance was good overall. These differences in performance are also generally statistically significant, despite the much smaller sample sizes compared to the aggregate pooled regression. Since our dependent variable is observed only one year after deal issuance, this suggests the differences in performance were observable even well before the onset of the financial crisis, when a significant volume of new deals were still being issued and rated.

Also presented in Table 7 are results of a simple "horse race", which compares side-by-side the relative predictive content of initial subordination and the model-projected default rate for variation in subsequent early-payment defaults. The table shows the regression R^2 obtained just from including the credit enhancement variables, and then the new R^2 after including either the two subordination variables, or the model default rate. The increase in explanatory power is almost always larger from the projected mortgage default rate. This may partially reflect the fact that our model is "tuned" to focus on early-payment defaults, rather than final losses. However, it still appears somewhat surprising, given that ratings incorporate a range of additional data and soft information not reflected in our model estimates.

7.3 Rating downgrades

Table 8 studies the determinants of post-issuance credit rating downgrades, as an alternative measure of deal performance. Rating downgrades are measured at the deal level by calculating the average net number of rating notches each tranche in the deal is downgraded between issuance and August 2009, weighted by original face value.[20] In principle, if initial ratings are set appropriately, ex-post rating revisions amongst different securities issued around the same time should not be easily predictable based on deal characteristics[21]. Systematically larger downgrades on MBS of a particular type (e.g. those from deals with a high share of low doc loans) suggests those deals were rated too generously initially.

While rating downgrades are used as the primary performance metric in several related papers on structured finance ratings (e.g. Adelino, 2009; Benmelech and Dlugosz, 2009; Griffin and Tang, 2009), a potential shortcoming of this measure is that the revised ratings may *also* be subject to systematic biases or errors. This caveat aside, however, studying rating downgrades does provide a useful robustness check on our analysis of defaults and losses on underlying mortgage collateral.

Table 8 regresses net weighted rating downgrades on the same credit enhancement variables, deal characteristics and time fixed effects employed in Table 6. Results for the key variables of interest match closely with our previous findings. Deals with a high share of low-documentation loans experience significantly larger credit rating downgrades both in the Alt-A and subprime sectors, significant in both cases at the 1% level. Deals with a high model-projected default rate also experience larger ex-post rating downgrades, significant at the 1% level in the Alt-A market, and marginally statistically significant for subprime deals.

7.4 Other performance measures

Table 9 presents results for two cumulative measures of ex-post mortgage performance, constructed using available LoanPerformance data as of August 2009. These are the cumulative realized loss

[20] e.g. A value of +3 would mean securities in the deal had been downgraded by a weighted average of three notches from issuance until August 2009, while -3 would indicate they had been *upgraded* by three notches.

[21] Note that rating changes may in fact be partially predictable if rating transitions are more volatile for certain securities, since ratings are truncated above at triple-A. We thank Dwight Jaffee for highlighting this point.

rate, and the cumulative mortgage default rate (defined as 90+ days delinquent, prepaid with loss or REO, as before) for the deal, both measured as a fraction of the original deal size.

Realized losses represent final losses of mortgage principal, due for example to shortfalls of the proceeds of a foreclosure or short sale relative to remaining mortgage face value. Realized losses are conceptually the closest measure to the size of final mortgage losses for the deal, which in turn determines how far up the capital structure bond investors will suffer losses of principal. However, because of lags involved in resolving delinquent loans, losses are realized only with a significant lag, which is a relative disadvantage of studying realized losses rather than defaults.

We use the same set of right-hand side variables as in Tables 6 and 8, relating deal performance to initial subordination, model-projected default, controls for credit enhancement, aggregated mortgage summary characteristics and a vector of year x quarter dummies. Results for both performance measures are again consistent with previous findings. Deals backed by observably risky collateral, reflected in a high model-projected default rate, experience significantly higher cumulative loss and default rates, controlling for initial subordination. (A 10% increase in the model-projected default rate is associated with higher losses and defaults of between 4-7%.) Conditional on the model-projected default rate, a 10% higher low-doc share increases losses and defaults by an additional 2-7%, depending on the specification. Coefficients on these two variables are statistically significant at the 1% level in all four specifications. Finally, while the relationship between initial subordination and cumulative losses and defaults is still generally positive, results appear weaker at these longer horizons than for the early-payment defaults studied in Table 6.

7.5 Summary and discussion

While our results suggest higher subordination (i.e. a lower fraction of highly-rated securities) is correlated with worse ex-post mortgage performance, as expected, our analysis also uncovers systematic performance differences amongst different types of deals from a given cohort. Two results stand out. Namely we find underperformance for MBS deals backed by *observably* risky loans, as measured by a simple ex-ante benchmark model, as well as deals with a high concentration of low- and no-doc mortgages. These stylized facts are robust to use of four different performance measures (early-payment defaults, rating downgrades, cumulative defaults and cumulative losses), and hold throughout the sample, not just for later vintages most affected by the crisis.

How should our findings be interpreted? We note that our ex-ante default model is based only on *observable* risk characteristics, such as FICO, LTV and DTI. It does not take into account soft information such as assessments of issuer and originator quality, or other judgmental adjustments. The predictive power of the model-projected default rate suggests relatively too little weight was placed on these observable risk characteristics in the rating process. This finding matches closely with Griffin and Tang (2009), who find that non-model adjustments to CDO credit ratings worsen rating quality.

As argued above, low-doc loans are likely to be more opaque and difficult to evaluate than other mortgage types, because of uncertainty about whether the borrower's income is self-reported truthfully or not. From this perspective, the disproportionately poor performance of deals backed by such loans appears consistent with theoretical predictions of Skreta and Veldkamp (2009) and Sangiorgi et al. (2009). A different interpretation is that CRA models did not reflect the progressively worsening credit quality of low-doc loans over this period (see Rajan, Seru and Vig, 2008, who document this trend and argue it is due to endogenous structural change in the borrower pool). Under either interpretation however, our results imply that ratings for low-doc deals were too generous, even relative to other types of deals. Since credit ratings are shown to significantly influence the cost of credit, it appears likely that overly optimistic credit ratings contributed to the unprecedented growth in low- and no documentation mortgages over our sample period.

8. Summary and conclusions

This paper presents the first comprehensive academic analysis of credit ratings on residential MBS issued in the period leading up to the recent financial crisis. Our evidence does suggest that ratings are informative, and also rejects a simple story that credit rating standards deteriorate uniformly over the pre-crisis period. However, we find evidence of apparently significant time-series variation in subordination levels; most robustly, we observe a significant decline in risk-adjusted subordination levels between the start of 2005 and mid-2007.

Our analysis also suggests MBS ratings did not fully reflect publicly available data. Observably high-risk deals, measured by a simple ex-ante model, significantly underperform relative to their initial subordination levels. Deals with a high share of low-documentation mortgages also perform disproportionately worse compared to other types of risky deals. These two results are evident even for earlier vintages, and can be identified even only using pre-crisis data.

Our results are not conclusive about the role of explicit agency frictions in the rating process. However, two of our results appear consistent with recent theoretical literature modeling these frictions: (i) the poor performance relative to ratings of deals backed by opaque low-documentation loans, and (ii) the observed decline in risk-adjusted subordination around the peak of MBS issuance, when incentive problems are likely most severe. Further analysis of the importance of explicit rating shopping and other incentive problems is, we believe, an important topic for future research.

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Appendix A: Definitions of Deal-level Regression Variables

Data sources: LoanPerformance (LP), Bloomberg, ABSNet, FHFA (formerly OFHEO).

Variable	Description	Source
Subordination below AAA, BBB- (percent)	One minus the ratio of the sum of face value of securities with rating of at least AAA or BBB- over the summed principal value of mortgages underlying the MBS deal.	LP, Blmbg, ABSNet
Projected default rate (percent)	Weighted average projected 90+ day default rate for mortgages underlying MBS deal, based on recursive loan-level model. Weighted by loan balance.	LP
Bond insurance dummy (0,1)	Dummy variable indicates whether at least one tranche in the deal was insured by a bond insurer. This is a form of external credit enhancement.	ABSNet
Fraction of deal with bond insurance (percent)	Percentage of the face value of the bonds in the MBS deal that are insured.	ABSNet
Weighted average coupon rate (percent)	Weighted average coupon rate on securities issued as part of the deal, weighted by original tranche face value.	ABSNet
Weighted mortgage interest rate (percent)	Weighted average interest rate on mortgages underlying the deal as of month of securitization, weighted by outstanding loan balance.	LP
Geographic concentration of loans	Sum across US states the squared fraction of loan balances in the deal that were originated in that state. Thus, the index is bounded between 0.02 and 1. Higher value indicates greater concentration.	LP
Number of ratings	Number of rating agencies that rated at least part of the deal, amongst Fitch, Moody's, S&P and DBRS.	ABSNet
Weighted average aggregated loan characteristics		
Low-documentation (percent)	Percentage of mortgage collateral consisting of low- or no-documentation mortgages (loans where borrower provides no or only partial documentation of their income, assets, occupation etc.)	LP
CLTV (percent)	Average combined reported loan-to-valuation ratio for all mortgage liens, as a percentage of the assessed property value.	LP
FICO	Average borrower credit score (FICO score). FICO scores range between 300 and 850. Higher values imply greater creditworthiness.	
HPA (percent)	Local percentage house price appreciation over the previous 12 months. Prices measured at the MSA for urban properties, or the state for loans from non-urban areas.	FHFA, LP
Interest-only (percent)	Weighted percentage of interest only loans. These are loans that involve no initial payments of mortgage principal by the borrower.	LP
Investor (percent)	Weighted percentage of the deal consisting of loans for non-owner-occupied properties.	LP

Appendix B: Dataset construction

Our empirical analysis is based on a novel dataset combining loan-level and security level information matched with house price and macroeconomic data. Our dataset covers 3,144 nonprime MBS deals issued between 2001 and 2007, reflecting 59,955 individual securities, and 12,074,103 underlying mortgage loans.[22]

Our dataset links information from several sources:

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

As well as loan-level data, LoanPerformance provides a deal identifier which allows us to aggregate the loans by issued deal. We also make use of a concordance provided by LoanPerformance between the LP deal identifiers and security CUSIPs, which permits a one-to-many merge between LP deals and the securities that make up the deal.

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 2008.

Bloomberg
We supplement our ABSNet security-level data with information from Bloomberg downloads. Most importantly, Bloomberg provides some additional information relative to ABSNet about the cash flow characteristics of individual securities, allowing us to correctly calculate subordination on each deal by screening out cases where we would otherwise double-count securities. This is detailed further below.

Macroeconomic data: home 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 OFHEO). We first match to the MSA-level house 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

[22] Note:The structure of our dataset is similar in many respects to the one independently developed by Nadauld and Sherlund (2009), whose analysis is based on a sample of 1,267 subprime deals issued between 1997-2007.

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

Step 1: Bloomberg preparation

We first extract all security-level from Bloomberg for non-agency RMBS, which we identify as securities which are not flagged as "Agency Backed", and which have tickers that match either "RES B/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 directly by mortgage loans. Consistent with this, none of these deals are linked to cash collateral via the security-level concordance provided to us by LoanPerformance. This produces a dataset with 157,993 tranches and 10,143 deals. (This is an overestimate of our population, because given the way Bloomberg defines security classes, many of these relate to prime-jumbo or agency MBS deals.)

Step 2: ABSNet preparation

Security-level data is collected from ABSNet for tranches listed in the "Home Equity" or "Residential MBS" asset class. Fields include the tranche face value, coupon, CUSIP identifier, and the history of security credit ratings from each of Moody's, S&P, Fitch and/or DBRS, as available. ABSNet data contains 123,006 tranches and 9,114 deals.

We determine the credit ratings at origination by identifying the earliest rating on a tranche within this history. We convert ratings for each CRAs into a standard numerical integer scale also used by Morgan (2002) and other papers (e.g. AAA = Aaa = 1, AA+ = Aa1 = 2 and so on).

Our regressions control for the security coupon rate at origination. Some securities have a fixed coupon rate, but most have a floating rate. Since the coupon rate on these securities is generally quoted as a spread to Libor, we calculate the coupon rate by adding back the six-month Libor rate as of the issuance data. In a small number of cases the 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 two quarters of the origination date. Otherwise, we estimate the margin on the tranche by differencing the six month Libor rate as of the date of the coupon, and then estimate the original coupon by adding the six month Libor at the date of deal origination.

Step 3: Merge LoanPerformance and macroeconomic data

Based on the state and zip-code identifiers in LP, we match each loan to local home price data from FHFA (formerly OFHEO). In particular, we merge the data with the local percentage house price appreciation over the previous 12 months. Prices measured at the MSA for urban properties, or the state for loans from non-urban areas, or for loans where no zip code is provided in LP. We also match each observation to the state unemployment rate for the month of origination.

Step 4: Estimate loan-level model and estimate projected default probabilities, using LP

As described in the text, we generate an simple ex-ante estimate of the default risk of each mortgage, based on a set of logit default regressions. These regressions are estimated using a random 10% LoanPerformance sample, and estimate the probability that a loan will be seriously (90+ days) delinquent one year after origination. We estimate these regressions on a rolling basis, where the end of the sample period is 9/2000, 3/2001, 9/2001, and so on, up to 3/2007. (Since a 12-month default history is required, a regression estimated using sample up to time T includes loans originated only up to T minus one year).

We then substitute each loan into the regression model estimated up to the six-month period *before* the issuance of the deal of which the loan is part. For example, if a loan is part of a deal issued between January and June 2005, we calculate the projected default rate for the loan using the regression model based on the sample up to September 2004. (Note that to be conservative, we reserve three months of data after the end of the sample period, to allow for data release lags. This is why, in this case, the model is estimated using a sample up to only September 2004, not December 2004.

Under this approach, the projected default rate for each loan is based only on historical data available at the time the deal is issued.

<u>Step 5: Aggregate LP loan-level data to the deal level</u>

We now aggregate LoanPerformance data and the default probabilities estimated in Step 4 to the deal level, using the identifiers provided in LP. When collapsing to the deal level, each variable is weighted by the closing loan balance as of the date of securitization, that is, according to the following formula:

$$var_i = \frac{\sum_{j\,\epsilon deal\, i} var_{i,j} * mortgage\ balance_j}{\sum_{j \epsilon deal\, i} mortgage\ balancej}$$

We also construct a measure of geographic diversification of the mortgage collateral underlying each deal. Specifically, we sum across US states the squared fraction of loan balances in the deal that were originated in that state. This measure, calculated the same way as a Herfindahl index, is bounded between 0.02 and 1. Higher value indicates greater geographic concentration of mortgages in the deal.

$$geographic\ concentration\ = \sum_{j \in states} (\frac{total\ mortgage\ principal\ in\ state\ j}{total\ mortgage\ principal\ balance})^2$$

<u>Step 6: Merge the data and drop negative amortization deals</u>

We then merge the Bloomberg, ABSNet, and aggregated LP data by CUSIP identifier.[23] We first require that any deal in the final dataset has tranche information from Bloomberg. Second, we eliminate any deals without LoanPerformance underwriting and performance data. Finally, we drop deals without a positive number of tranches with rating data from ABSNet. For our analysis, we also drop out deals that include negative amortization mortgages, and deals that are not issued between 2001 and 2007, inclusive. This leaves a final sample of 59,955 individual securities from 3,144 different deals.

<u>Step 7: Calculate subordination for each deal</u>

We then calculate subordination at the AAA and BBB- attachment points for each of the deals in our sample, according to the following formula:

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

---

[23] One reason why the security and deal counts are different across our different datasets is that the non-prime market coverage of Bloomberg and ABSNet is more comprehensive than LoanPerformance, especially prior to 2003. Second, the composition of deal types is different across the three vendors. In particular, the population of Bloomberg and ABSNet securities we consider includes a significant volume of prime private-label prime MBS.

We use the earliest rating provided in ABSNet to calculate subordination. We also cross-check these initial ratings against the attachment point of "A-level" tranches provided in Bloomberg. In cases of split ratings, we use the more conservative rating. Split ratings are rare around the AAA attachment point, although more common at the investment grade boundary (BBB-).

To avoid double-counting when summing the face value of securities, certain security categories with a notional face value are recoded as having a face value of zero for the purposes of the sum in the above formula. These arise when the deal includes support bonds, such as interest-only (IO) tranches or prepayment tranches.[24] 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: (i) Notional ("NTL", "NOTIONAL_PRINCIPAL", "IO", INTEREST_ONLY_CLASS"); (ii) Prepayment Tranches ("PIP", "PREPAYMENT_PENALTY"); (iii) Exchangeable ("EXCH", "EXE"); (iv) Residual Tranches ("RESIDUAL", "R", "OC", "OVER-COLLATERALIZATION"); (v) Subordinated ("SUBORDINATED_BOND").

Step 8: Construct credit enhancement measures

As described in the text, our deal-level regressions control for a number of other types of credit enhancement, including the geographic concentration of loans in the deal, the coupon rate and mortgage interest rate. The insurance flag is taken from the Bloomberg data. We generate both a dummy variable for presence of insurance on any tranche in the the deal, as well as a variable measuring the fraction of the face value of the deal that is insured.

Step 9: Label each deal as either subprime or Alt-A

There is no single consistent definition of subprime or Alt-A loans or deals in either the mortgage industry or the academic literature. Generally, subprime loans are considered to be of the lowest credit quality, and will generally have the poorest underwriting characteristics, such low FICO scores and high LTV and DTI ratios. Alt-A loans have stronger average underwriting characteristics, and are made to borrowers with stronger credit histories. However, they are more likely to include risky contract features or limited documentation (i.e. a higher fraction of low- and no-documentation, interest-only, and negative amortization mortgages). Of our datasets, LoanPerformance is the only one that identifies loans and deals as specifically subprime or Alt-A. Therefore, we consistently use this LP definition for splitting our sample into subprime and Alt-A deal subsamples.

[24] To see why this is necessary, consider the case of interest-only tranches, which arise when the principal and interest payments from a mortgage pool 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, each rated AAA, and an equity tranche of $100bn. The correct AAA subordination level in this example is 10%. However, 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. A similar argument applies to prepayment tranches, which receive unscheduled but not scheduled payments of principal.

Figure 1: Credit rating downgrades by vintage

Figure plots average net nonprime MBS ratings revisions by calendar quarter of deal issuance. Covers subprime and Alt-A deals in our sample issued between Q1:2001 and Q4:2007. Y-axis measures the average net number of rating notches that securities issued in calendar quarter have been downgraded between issuance and August 2009, weighted by security original face value. [e.g. A security downgraded from AA+ to A- is recorded with a value of +5 since the security has been downgraded by five notches: from AA+ to AA, AA-, A+, A, A-.] A negative value means securities have on average been upgraded since issuance. For securities with multiple ratings, the net rating change is a simple average across ratings. Moody's ratings are based on a 21-notch scale (Aaa to C), while ratings for S&P, Fitch and DBRS are based on a 22-notch scale (AAA to D). Vertical lines correspond to the period Q1:2005 to Q2:2007, the period of peak MBS deal flow.

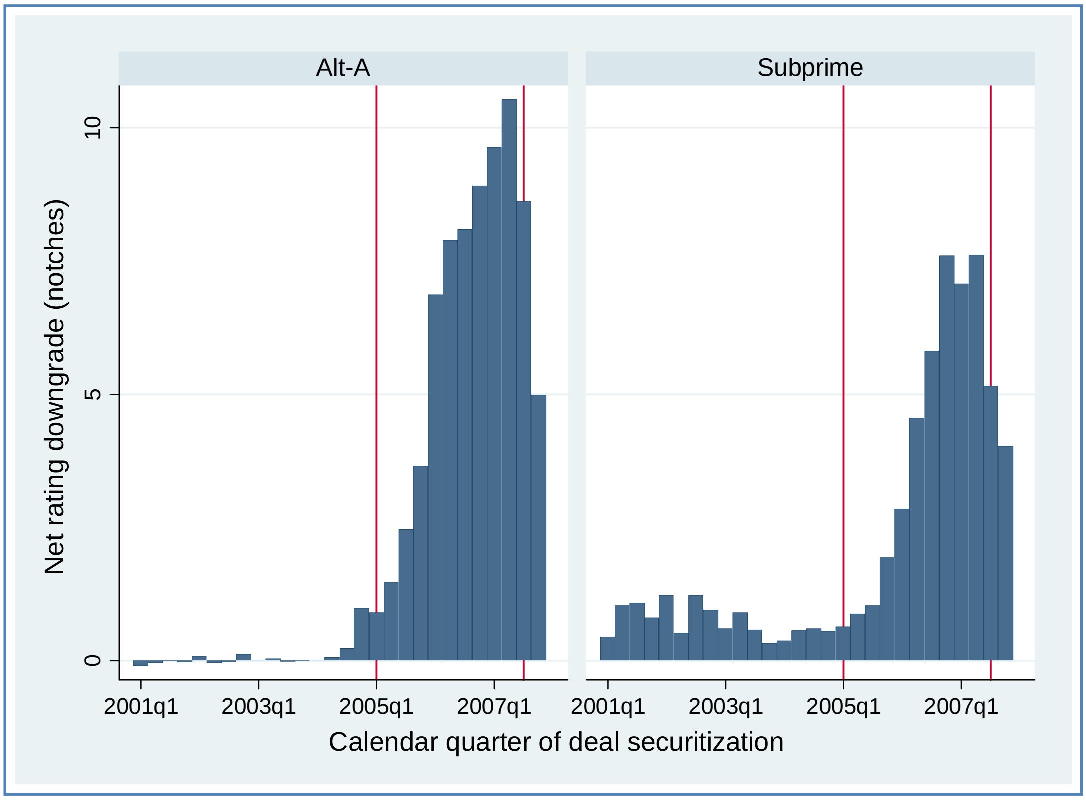
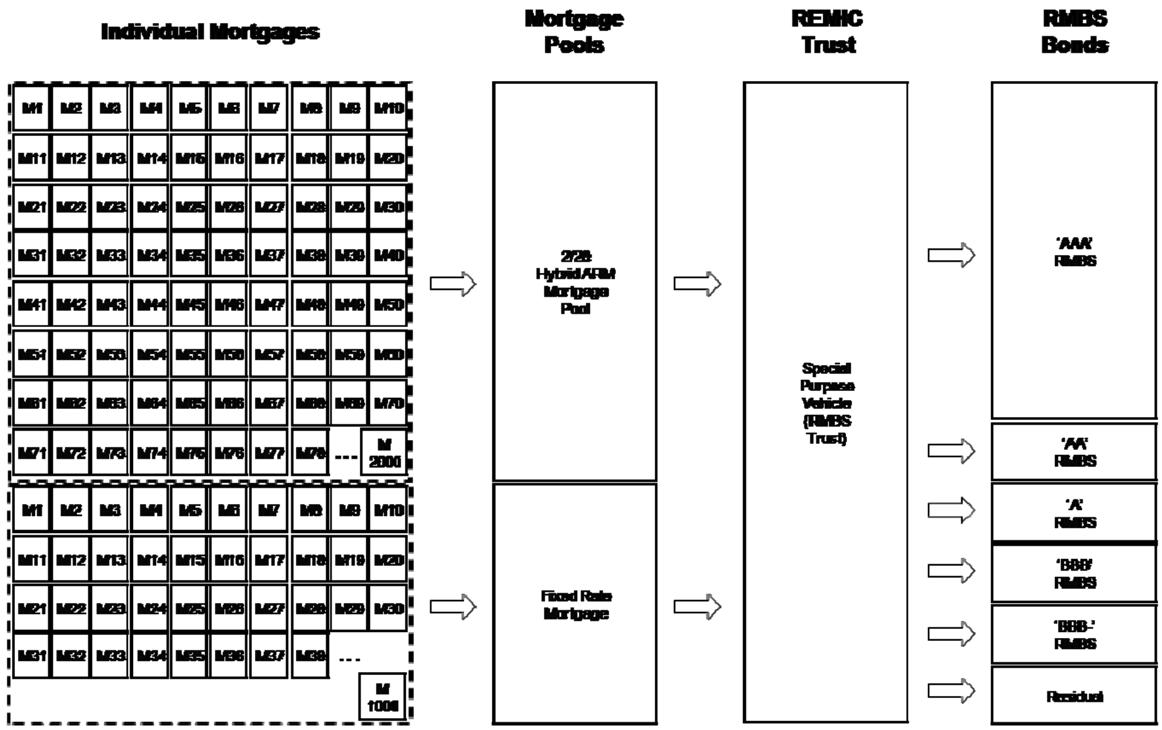


Figure 2: Structure of a non-agency MBS deal

In a typical non-agency MBS deal, individual mortgages are combined into one or more pools inside a bankruptcy-remote special purpose vehicle known as a REMIC trust. Mortgage-backed securities are then issued with claims to the cash flows of these mortgage pools. MBS deals have a "senior-subordinated structure" which means securities are ordered in terms of seniority with respect to principal payments on mortgages held 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. Although the diagram depicts only a single AAA security, usually there will be multiple AAA tranches, which together form the A-class of the deal. A typical deal contains 15-20 tranches in total.



Source: Moody's.

Figure 3: Evolution of MBS deal flow

Figure plots the number of subprime and Alt-A MBS deals issued by calendar quarter over the period 2001-2008, as well as the total face value of securities issued each quarter, based on our sample. It also plots total securities issuance volume as reported in the industry publication Inside Mortgage Finance. A comparison between the two volume figures suggests our dataset captures a large fraction of total MBS origination volume over this period. (Coverage is somewhat lower for Alt-A, because we drop negative amortization deals from our sample). Vertical lines correspond to the period Q1:2005 to Q2:2007, the period of peak MBS deal flow.

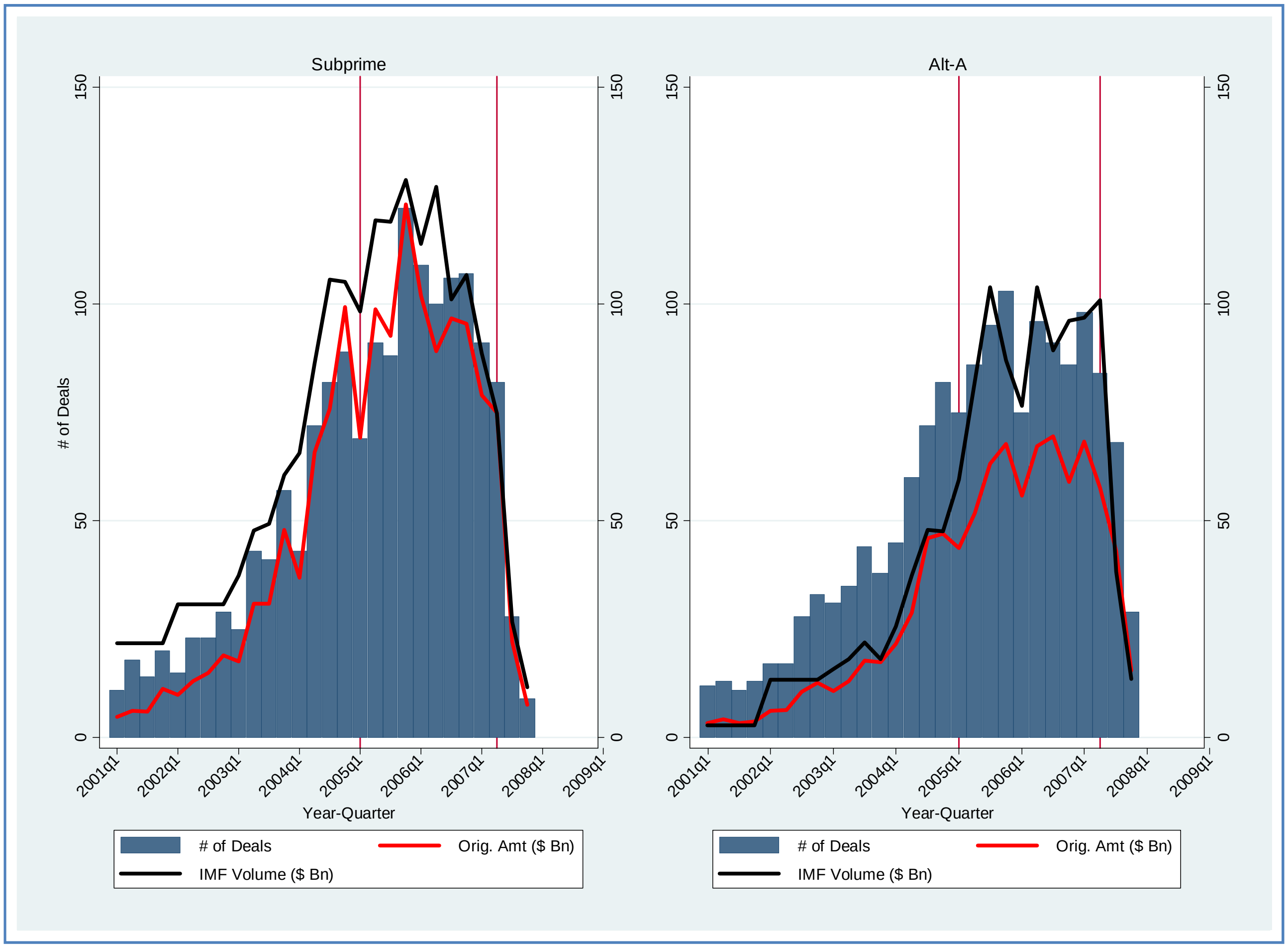


Figure 4: Time-series trends in credit ratings

Figure plots the time-series evolution of average unconditional subordination below three rating classes (AAA, A and BBB) for subprime and Alt-A deals. Higher subordination means a more conservative credit rating for the deal. (See text for full definition.) Subordination levels are constructed from ABSNet, Bloomberg and LoanPerformance data for our sample of 3,144 deals. Vertical lines correspond to the period Q1:2005 to Q2:2007, the period of peak MBS deal flow.

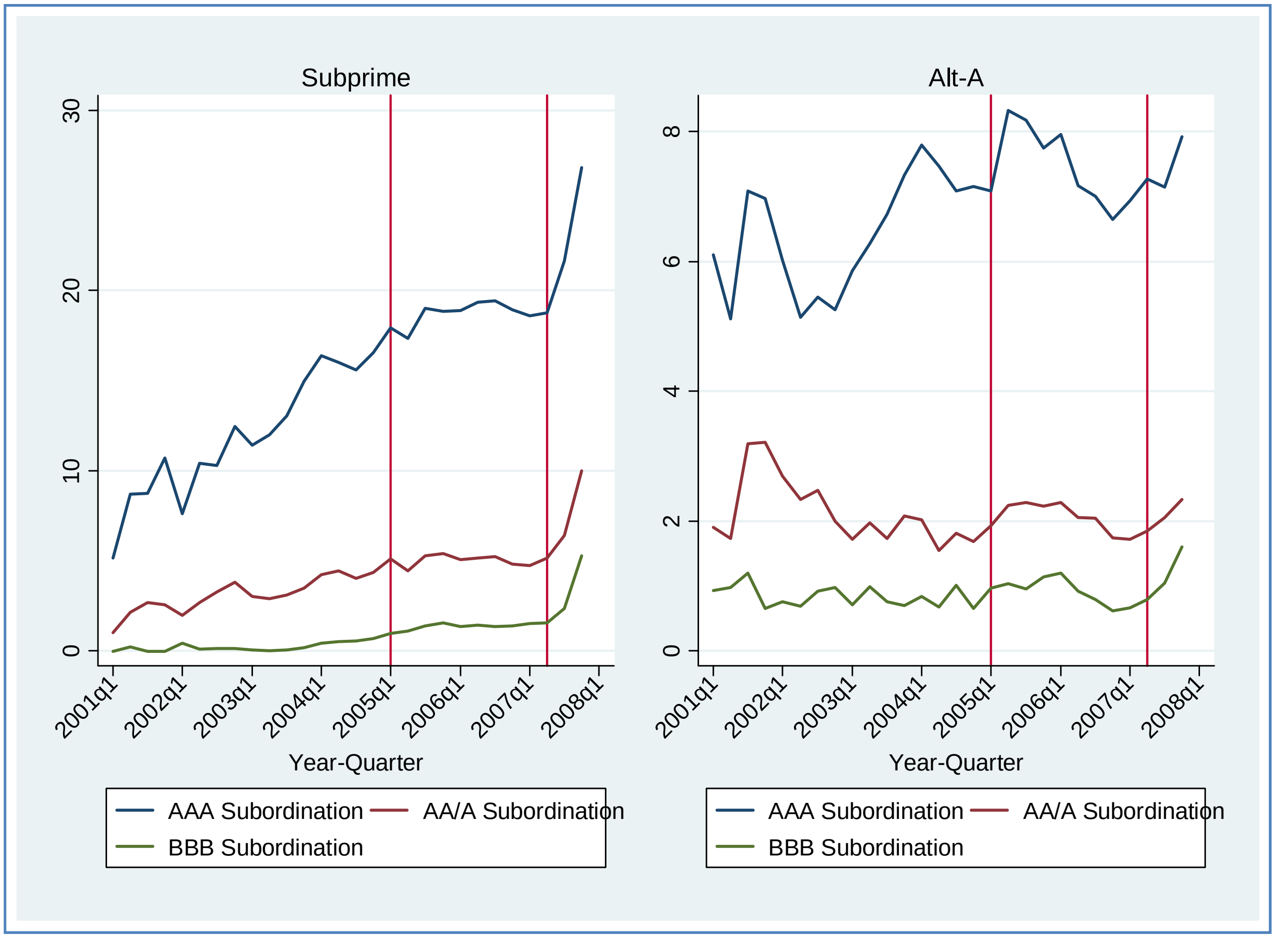


Figure 5: Projected and realized mortgage delinquency rate, by vintage

The dashed line in the Figure is the average projected 12-month 90+ mortgage delinquency rate, by deal vintage (i.e. by the calendar quarter in which the deal was issued). This projection is based on the backward-looking loan-level default model described in the text. The solid line is the average *realized* 90+ delinquency rate for the same vintage one year later. Note: The 12-month 90+ delinquency rate refers to the weighted fraction of mortgages that are delinquent by at least three monthly payments, one year after the deal is issued.

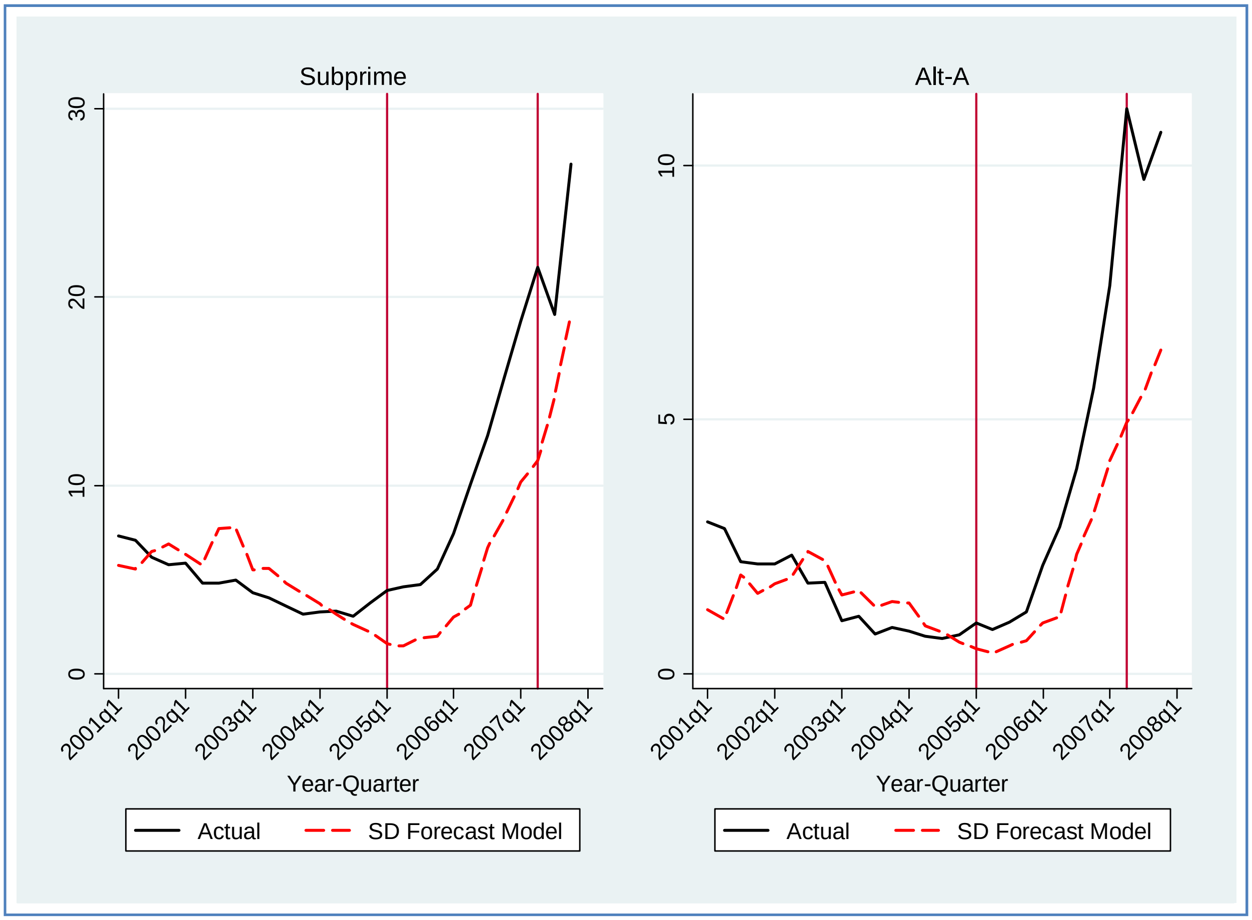
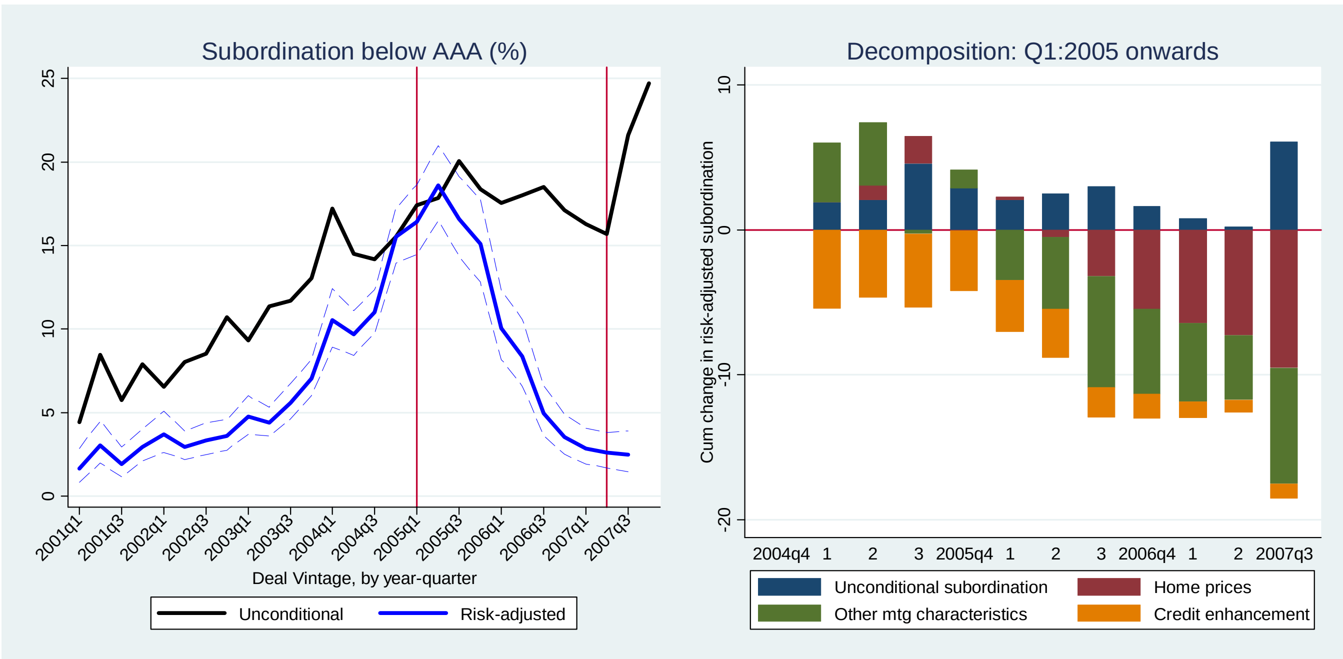


Figure 6: Trends in MBS ratings after controlling for risk

The two left-hand panels present conditional and risk-adjusted AAA subordination for subprime and Alt-A deals, respectively. Risk-adjusted subordination reflects residual changes in credit ratings after controlling for the variables in Table 5 (such as the model-projected default rate, insurance dummy etc.) The two right-hand panels decompose the sources of the cumulative change in risk-adjusted divergence since 2005:Q1.

Panel A. Subprime deals



Panel B. Alt-A deals

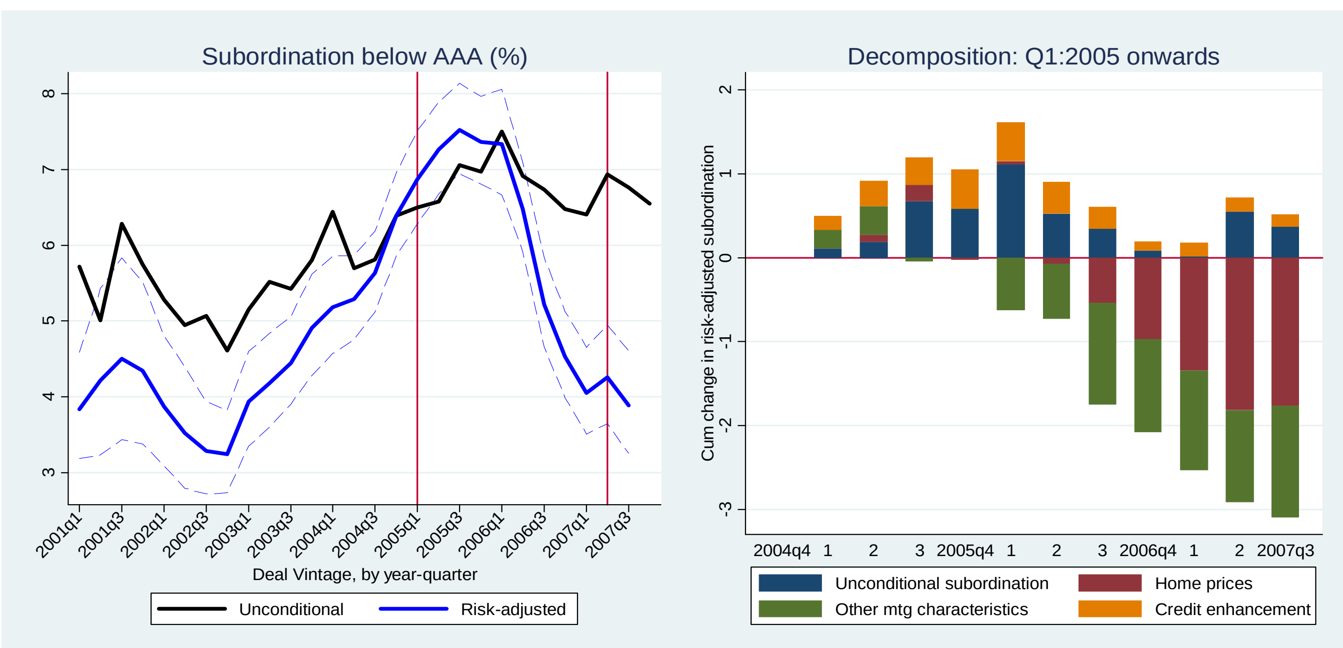


Table 1. Deal characteristics

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. 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
25th percentile	509	313	391
50th percentile	790	487	631
75th percentile	1120	756	960
Fraction of AAA (%)			
Mean	82.4	93.1	87.6
25th percentile	79.1	92.4	81.4
50th percentile	81.7	93.9	89.3
75th 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 (FHFA)	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 (%, FHFA)	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. Logit regression, based on a 10% LoanPerformance sample of mortgages originated between April 1992 and December 2007. In paper, this specification is estimated recursively using different subsamples of data, to construct a projected default rate for each deal based only on data from before deal was issued.

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 (%)	0.0286***
	(0.00334)
FICO	-0.0105***
	(0.000265)
12-month trailing HPA (%)	-0.000535***
	(0.0000619)
Balloon loan (1=yes)	0.00119***
	(0.000150)
Low Doc (1=yes)	0.00532***
	(0.000324)
No Doc (1=yes)	0.00743***
	(0.000504)
Investor (1=yes)	0.00406***
	(0.000287)
Debt-payments-to-income (DTI)	0.00990***
	(0.000489)
DTI Missing	0.00254***
	(0.000290)
Cashout Refinance (1=yes)	-0.00356***
	(0.000235)
ln(loan amount)	0.500***
	(0.0456)
Prepayment Penalty (1=yes)	0.00364***
	(0.000140)
Local unemployment rate (%)	0.00543
	(0.00827)
Spread at Origination (SATO, %)	0.121***
	(0.0304)
Other covariates	
Dummies for missing values of other variables	yes
Year-half dummies	yes
N (10% LP sample)	1309495
Unconditional mean of dependent variable	0.0602
Pseudo R-Squared	0.1497

Table 5. Determinants of AAA subordination

Deal-level regression of the determinants of AAA subordination, based on full sample of 3,144 deals. "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 calendar period in which the deal was issued. Standard errors clustered by year x quarter. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Dependent variable: ln(1 + % subordination below AAA class).

	Subprime		Alt-A	
Mortgage 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+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***
Include aggregated loan-level variables	No	Yes	No	Yes
Joint significance: F-Test (p-value)		0.1440		0.0000***
Other deal characteristics				
Bond insurance (1=yes, 0=no)	-0.473***	-0.478***	-0.0250	0.00370
	(0.100)	(0.100)	(0.0395)	(0.0376)
Percentage 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)
Time-series variation in subordination				
Year x quarter dummies	Yes	Yes	Yes	Yes
F-test: ratings decline over 2005-07? (p-value)[a]	0.0000***	0.0000***	0.0000***	0.0388**
Number of observations	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 second half of the "credit boom" period (2005:01 to 2007:Q2) is equal to its value in the first half of this period.

Table 6: Credit ratings and early-payment mortgage defaults

Linear regression. 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. R^2 is based on variation in the data within year-quarters. Standard errors clustered by year x quarter. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Dependent variable: ln(1+% deal in default 12 months after deal is issued)

	Subprime deals			**Alt-A deals**		
Include covariates	No	Yes	Yes	No	Yes	Yes
Credit boom (Q1:05-Q2:07) interactions	No	No	Yes	No	No	Yes
Credit ratings						
ln(1+% subordination below AAA)	0.112***	0.112***	0.118***	0.198***	0.0505	0.0553*
	(0.0340)	(0.0305)	(0.0325)	(0.0378)	(0.0344)	(0.0317)
ln(1+% subordination below BBB-)	0.0955***	0.0645***	0.0552***	-0.144***	-0.0960***	-0.0794***
	(0.0157)	(0.0144)	(0.0134)	(0.0423)	(0.0241)	(0.0234)
Model-projected mortgage default rate						
ln(1+projected default rate)	0.941***	1.004***	0.837***	1.470***	1.523***	1.503***
	(0.0622)	(0.0567)	(0.0522)	(0.102)	(0.0422)	(0.0610)
ln(1+default rate) * "boom" dummy			0.317***			0.0724
			(0.0939)			(0.115)
Fraction of low documentation mortgages						
% of low/no-doc mortgages		0.00681***	0.00327***		0.00290***	0.00267***
		(0.000656)	(0.000852)		(0.000792)	(0.000839)
% low/no doc * "boom" dummy			0.00568***			0.000607
			(0.00115)			(0.00128)
Other deal characteristics						
Bond insurance (1=yes)	3.35e-05	0.000129	0.00554	-0.0120	0.0237	0.0261
	(0.0438)	(0.0334)	(0.0323)	(0.0358)	(0.0329)	(0.0320)
% of deal with bond insurance	0.00177*	0.00131*	0.00133**	-0.00112	-0.00221**	-0.00192*
	(0.000872)	(0.000664)	(0.000623)	(0.00117)	(0.00104)	(0.000992)
Weighted average coupon rate (%)	-0.0243	-0.0112	-0.0500**	-0.0264**	0.0105	0.00340
	(0.0222)	(0.0221)	(0.0190)	(0.0124)	(0.00964)	(0.0106)
Weighted mortgage interest rate (%)	-0.0762***	-0.130***	-0.122***	0.0613	0.0184	0.00422
	(0.0105)	(0.0152)	(0.0154)	(0.0428)	(0.0265)	(0.0280)
Geographic concentration of loans	0.475**	0.0635	0.0540	-0.133	-0.239**	-0.241**
	(0.194)	(0.203)	(0.196)	(0.107)	(0.101)	(0.0953)
Dummies for number of credit ratings (omitted category: three ratings)						
One Rating		0.213***	0.305***		-0.0161	-0.0581
		(0.0343)	(0.0392)		(0.0343)	(0.0392)
Two Ratings		0.0108	0.0505*		0.0366*	0.00127
		(0.0149)	(0.0268)		(0.0149)	(0.0268)
Four Ratings		0.113***	0.106***		0.0620	0.0976
		(0.0290)	(0.0275)		(0.0290)	(0.0275)
Other loan-level covariates						
Average CLTV (%)		0.00889***	0.00715***		0.0188***	0.0182***
		(0.00188)	(0.00169)		(0.00130)	(0.00160)
FICO		0.000279	0.000302		0.00143***	0.00145***
		(0.000469)	(0.000486)		(0.000230)	(0.000219)
12 month trailing HPA (%)		-0.00279	-0.00245		0.00857	0.00751
		(0.00815)	(0.00753)		(0.00539)	(0.00550)
% of interest only loans		-0.000429	-0.000990		0.00155**	-0.000256
		(0.000515)	(0.000765)		(0.000608)	(0.000649)
% of investor loans		0.00430*	0.0212***		0.00190**	-0.000272
		(0.00230)	(0.00454)		(0.000814)	(0.00111)
Boom x IO, investor, num ratings	no	no	yes	no	no	yes
Year x quarter dummies	yes	yes	yes	yes	yes	yes
N	1607	1607	1607	1537	1537	1537
R^2	0.521	0.594	0.613	0.640	0.741	0.747

Table 7: Subordination and early-payment defaults, cohort regressions

Year by year regression of deal-level mortgage default rate on subordination, model-projected default and fraction of low-documentation mortgages, and other deal controls as in Table 6: two bond insurance variables, average coupon rate and mortgage interest rate, and measure of geographic diversification of pool (coefficients omitted to conserve space). Standard errors clustered by 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.***, ** and * represent significance at 1%, 5% and 10% levels.

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

	Vintage						
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
A. Subprime deals							
Baseline specification: including credit ratings, model default and low doc							
ln(1+% subordination below AAA)	0.00256	-0.0328	0.0387	0.119**	0.129*	0.310*	0.188*
	(0.0781)	(0.0281)	(0.0749)	(0.0288)	(0.0479)	(0.122)	(0.0628)
ln(1+% subordination below BBB-)	0.107**	0.0116	0.152*	0.0694**	0.0386**	-0.0298	0.0245
	(0.0291)	(0.109)	(0.0518)	(0.0161)	(0.0116)	(0.0204)	(0.0533)
ln(1+projected default rate)	0.969***	0.616**	0.642***	0.716***	1.314***	0.794**	1.039***
	(0.160)	(0.153)	(0.104)	(0.0940)	(0.0330)	(0.243)	(0.0238)
% of low/no-doc mortgages	0.00917	0.0146**	0.00457**	0.00556***	0.00810***	0.00664***	0.00789**
	(0.00443)	(0.00321)	(0.00102)	(0.000315)	(0.00119)	(0.00102)	(0.00180)
R^2	0.875	0.806	0.564	0.542	0.564	0.628	0.756
N	63	90	166	286	370	422	210
Explanatory power of different specifications (measured by R^2)							
Just deal controls	0.341	0.409	0.309	0.195	0.026	0.402	0.260
Deal controls and subordination	0.520	0.424	0.359	0.365	0.154	0.487	0.559
Deal controls and projected default	0.856	0.716	0.516	0.413	0.449	0.550	0.674

	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
B. Alt-A deals							
Baseline specification: including credit ratings, model default and low doc							
ln(1+% subordination below AAA)	-0.0473	-0.0221	0.0481	0.0969*	0.380**	0.303***	0.0274
	(0.159)	(0.0381)	(0.0335)	(0.0379)	(0.0708)	(0.0482)	(0.0972)
ln(1+% subordination below BBB-)	-0.00240	-0.150	-0.0746	-0.0771	-0.111	-0.124	-0.206
	(0.0593)	(0.172)	(0.0676)	(0.0446)	(0.0488)	(0.0880)	(0.108)
ln(1+projected default rate)	0.198	1.106**	1.186***	0.833***	1.089**	1.463***	1.869***
	(0.375)	(0.253)	(0.114)	(0.136)	(0.326)	(0.177)	(0.0477)
% of low/no-doc mortgages	0.00560	0.00420**	0.00356*	0.00117	0.00258	0.00509**	0.00815
	(0.00389)	(0.00121)	(0.00143)	(0.000820)	(0.00119)	(0.00131)	(0.00466)
R^2	0.843	0.830	0.798	0.632	0.655	0.650	0.739
N	49	95	148	259	359	348	279
Explanatory power of different specifications (measured by R^2)							
Just deal controls	0.779	0.696	0.598	0.450	0.338	0.368	0.273
Deal controls and credit ratings	0.786	0.699	0.603	0.496	0.547	0.451	0.343
Deal controls and projected default	0.818	0.809	0.775	0.612	0.534	0.622	0.706

Table 8: Determinants of credit 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: Credit rating downgrades (notches, value-weighted average)

	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)
Projected default and concentration of low documentation loans				
ln(1+projected default rate)	0.817*	0.748	2.595***	3.066***
	(0.472)	(0.597)	(0.909)	(0.948)
% of low/no-documentation mortgages		0.0444***		0.0151***
		(0.0133)		(0.00521)
Other deal characteristics				
Bond insurance (1=yes)	-0.379	-0.309*	-0.707**	-0.621*
	(0.226)	(0.160)	(0.342)	(0.345)
% 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)
Weighted 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)
Dummies for number of credit ratings (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)
Other loan-level covariates				
Average CLTV (%)		0.0377		0.0290*
		(0.0237)		(0.0162)
FICO		0.000947		0.00499***
		(0.00208)		(0.00163)
12 month trailing HPA (%)		-0.166**		0.109**
		(0.0713)		(0.0500)
% of interest only loans		0.00183		0.00780
		(0.00550)		(0.00600)
% of investor loans		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. Additional 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.

Dependent variable:	**ln(1+% cumulative losses)**		**ln(1+% cumulative defaults)**	
Market segment:	**Subprime**	**Alt-A**	**Subprime**	**Alt-A**
ln(1+% subordination below AAA)	0.0397	0.0689	0.0525*	0.104***
	(0.0263)	(0.0502)	(0.0303)	(0.0312)
ln(1+% subordination below BBB-)	0.124***	-0.0402**	0.0374**	-0.0412
	(0.0191)	(0.0189)	(0.0163)	(0.0290)
Projected default and concentration of low documentation loans				
ln(1+projected default rate)	0.369***	0.684***	0.653***	0.731***
	(0.0668)	(0.0726)	(0.0834)	(0.0713)
% low/no-doc mortgages	0.00779***	0.00187***	0.00489***	0.00394***
	(0.00141)	(0.000629)	(0.000874)	(0.000735)
Controls and other covariates				
Deal characteristics	Yes	Yes	Yes	Yes
Mortgage summary covariates	Yes	Yes	Yes	Yes
F-test: [p-value]	0.0000***	0.0000***	0.0000***	0.0000***
Year x quarter dummies	Yes	Yes	Yes	Yes
N	1567	1461	1567	1461
R^2	0.516	0.611	0.282	0.674