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SECURITIZATION AND MORTGAGE DEFAULT

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ABSTRACT

We find that private-securitized loans perform worse than observably similar, nonsecuritized loans, which provides evidence for adverse selection. The effect of securitization is strongest for prime mortgages, which have not been studied widely in the previous literature and particular prime adjustable-rate mortgages (ARMs): These become delinquent at a 30 percent higher rate when privately securitized. By contrast, our baseline estimates for subprime mortgages show that private-securitized loans default at lower rates. We show, however, that "early defaulting loans" account for this: those that were so risky that they defaulted before they could be securitized.

Keywords: Mortgage default, securitization, adverse selection

JEL Codes: D82, G21

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SECURITIZATION AND MORTGAGE DEFAULT

1. INTRODUCTION

One of the notable innovations of the mortgage boom was the dramatic increase in private securitization. By 2005, it made up more than 50 percent of all new securitizations.[1] This has been tied to a dramatic expansion in the provision of mortgage credit, particularly to segments of the population that had not been served in the past, such as subprime borrowers. Conversely, the dramatic increase in mortgage default rates following the collapse of the subprime bubble has led many to blame securitization. It is commonly asserted that issuers had less incentive to screen those loans that were sold to securitized pools and that this encouraged a decline in lending standards. This argument has been featured prominently in the popular press and has been echoed by policymakers. For example, the recently released U.S. Treasury report on regulatory reform notes that "[t]he lack of transparency and standards in markets for securitized loans helped to weaken underwriting standards," and the report goes on to propose that issuers be required to maintain a 5 percent stake in any securitization.[2] This has also been supported in recent academic work, for example, Mian and Sufi (2009), and Keys et al. (2009).

On the other hand, others (most prominently, Gorton, 2008) have pointed out that issuers retained substantial exposure to the mortgages that they securitized. Some of this was explicit since issuers often continued to service mortgages they had sold, or they retained senior tranches of CDOs containing these mortgages. But it was also implicit; the clearest evidence of this can be found in the credit card ABS market. For example, Gorton and Souleles (2007) show that prices paid by investors in credit card ABS take into account issuers' ability to bail out their ABS. Thus, issuers' incentives need not necessarily be misaligned with those of investors. This

[1] Source: Inside Mortgage Finance
[2] http://www.financialstability.gov/docs/regs/FinalReport_web.pdf

view is also supported by earlier work on the securitization of prime mortgages, in particular Ambrose et al. (2005), who found that securitized loans tended to perform *better* than similar nonsecuritized loans.

Several theories have been proposed for why lenders securitize loans. One is *regulatory arbitrage*; i.e., lenders sell loans to remove them from their balance sheets and thereby conserve costly capital (James, 1987). The second one suggests that securitization serves to reduce the scope of assets subject to bankruptcy costs (Gorton and Souleles, 2007). With both of these motivations, there is generally an incentive to securitize *safer* assets. In the case of regulatory arbitrage, this is because regulations assign the same capital charge to broad classes of assets, and in the latter case, because safer assets make it easier to design bankruptcy-remote structures.

By contrast, two other motivations for securitization imply that riskier loans would be sold. The first is *risk-sharing,* or diversification, particularly of interest-rate, credit, or house-price risk (Kendall, 1998). A final reason why riskier loans might be securitized is *adverse selection*, or cream-skimming. That is, there is a desire on the part of lenders to take advantage of private information that is available to them but not to potential investors (see for example, Demarzo and Duffie, 1999, and Parlour and Plantin, 2008). In contrast to securitization motivated by risk-sharing, however, such loans will be riskier even *after* controlling for observable information available to investors.[3]

In this paper, we first show that for prime mortgages that originated in 2005 and 2006, private-securitized loans do indeed perform significantly worse than non-private-securitized loans, after conditioning on publicly available information. This is consistent with adverse selection (i.e., lenders securitized loans that were unobservably riskier). Given that the vast

[3] Another reason why portfolio and securitized loans may perform differently is monitoring. This is discussed further below.

majority of mortgages originated over this time period were indeed prime loans (80 percent), this result is important to understand the true contribution of securitization to the financial crisis.

We then look at the performance of subprime loans originated in this time period. And while our baseline results indicate that private-securitized subprime loans defaulted at lower rates than portfolio loans, we show that this is explained by "early defaulting" loans. Lenders may well have originally intended for these loans to be sold to securitized pools, but they were not able to do so because the loans defaulted *before* they had a chance to sell them. After taking this into account, we find an insignificant relationship between securitization and default risk for subprime loans.

We also investigate the interaction between private securitization and the documentation type of the mortgage. As Keys et al. (2009) suggest, the asymmetry of information between lenders and investors is likelier to be more pronounced for low documentation loans, and thus one might expect a stronger effect from securitization. This is indeed what they find for subprime ARMs. We confirm the results of Keys et al. (2009) for our sample of subprime ARMs. However, we do not find a significant interaction between documentation type and private securitization for our other subsamples. Thus, further research should be undertaken to determine the extent to which these findings may be generalized.

Since the data that we use do not contain information on secondary markets, we cannot completely rule out the possibility that investors understood that such a deterioration in standards had taken place and that either the prices paid for the securities[4] or the structure of the mortgage-backed securities (MBS) reflected this additional risk (see Gorton and Souleles, 2007, for an example of this in credit card securitizations, and Adelino, 2009). Nevertheless, even if this were the case, securitization motivated by adverse selection could still be inefficient, as bad loans

[4] We do control for the interest rates on the individual loans.

would drive out the good — restricting lenders to more expensive on-balance-sheet financing to fund high-quality loans.

The remainder of the paper is organized as follows. Section 2 describes the related literature. Section 3 describes our data. Section 4 sets our methodological approach. Section 5 gives the results of our estimations. Section 6 concludes.

2. RELATED LITERATURE

This paper is not the first to examine the impact of securitization on default risk. One strand of the literature, most notably Mian and Sufi (2009), compares zip-code level securitization with default rates.[5] They find that those regions in which subprime securitization expanded most rapidly were also those in which default rates subsequently increased the most. However, their focus is on explaining aggregate trends rather than on explaining the default risk of individual mortgages. In particular, without detailed information on loan characteristics, an approach that uses aggregate data does not allow one to easily distinguish the risk-sharing motivation for securitization from adverse selection.

Other papers have used loan-level information to study the effect of securitization. The most prominent of these is Keys et al. (2009). This paper use loan-level data but only for securitized loans (from the Loan Performance [LP] ABS database). Thus, they must use an instrumental variables approach to characterize loans that are "harder" to securitize (those with credit scores just below 620) and find that these loans are indeed less likely to default, ceteris paribus. Although this is an ingenious approach that also addresses the issue of the endogeneity of securitization (discussed further below), several issues arise.

[5] See also Calem, Henderson, and Liles (2010).

First, some have argued that this instrument is relatively weak, since many subprime MBS did indeed contain substantial numbers of loans below this cutoff. For example, in the New Century securitization studied by Ashcraft and Schuermann (2008), 57 percent of all loans have FICO scores below 620. Furthermore, work by Bubb and Kaufman (2014) shows that this "620-discontinuity" also plays a role in underwriting nonsecuritized loans, which, they suggest, makes it difficult to use to make inferences on the link between securitization and adverse selection.

From the perspective of this paper, however, the key limitation of the analysis in Keys et al. (2009) is that they can examine only the effect of securitization for a narrow subset of loans — those in the neighborhood of their cutoff. By contrast, our approach allows us to examine a much broader segment of the mortgage market. In particular, our main result — that *prime* securitized loans are the ones in which the negative impact of securitization was greatest — could not be established by using an approach that requires restricting attention to loans with FICO scores around 620.

Ambrose et al. (2005) was the first of the papers that are similar to ours in both question and methodology. Looking at loans that originated by a single lender between 1995 and 1997, they compare the conditional default rates on securitized and nonsecuritized loans. As previously discussed, they find that securitized loans default at lower rates than nonsecuritized loans and conclude that either securitization is motivated by regulatory arbitrage or that reputational incentives are sufficiently strong to keep lenders from taking advantage of their information. These results are different from ours, but our paper considers a much larger set of loans, originated by many different lenders, and we focus on a time period in which the volume of risky lending (and subsequently, defaults) rose dramatically.

Extending the work of Ambrose et al. (2005), Krainer and Laderman (2014) use the Lender Processing Services (LPS) data to study the securitization decision, as well as the relation between securitization and the ex-post performance of loans that were originated in California from 2000–2007. First, they find that observably riskier loans were securitized (as do Jiang et al., 2014, discussed below). Regarding ex-post performance, they find that ARMs that were privately securitized are 13 percent to 16 percent more likely to default. This is qualitatively similar (albeit smaller in magnitude) than the results that we find for prime ARMs below. However, unlike us, they find that fixed-rate mortgages (FRM) are actually less likely to default. We can explain the difference between our results and theirs because they do not break out prime and subprime loans separately, and they do not account for early default; as we show below, this leads to a significantly riskier pool of subprime portfolio loans.

Agarwal et al. (2012) use fixed-rate loans from LPS and other data sets to study the determinants of the securitization decision and the performance of loans securitized by the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac and private-securitized loans, relative to those held in portfolio. They show that, until 2007, prime GSE loans tended to default at lower rates (and prepay at higher rates) than conforming loans held in portfolio. For prime jumbo loans, they similarly show that private-securitized loans prepaid at higher rates, whereas there is no significant difference in default rates. For subprime loans, they find no significant relationship between securitization and either default or prepayment.

Agarwal et al. (2012)'s results on the lower default rates for GSE loans mirror those in our paper. There are, however, some significant differences with ours. First, they do not consider ARMs; we show that this is the segment for which securitization has the greatest impact on default rates. In addition, they only consider binary comparisons between either GSE or private-securitized loans on one hand and portfolio loans on the other. Finally, we show the importance of early default on the interaction between default rates and private securitization in the subprime market.

Lastly, Jiang et al. (2014) use data on loans originated by a single lender between January 2004 and February 2008 (primarily low-documentation Alt-A loans and subprime mortgages). They find that, while securitized loans were observably riskier than loans retained by lenders (based on ex-ante information available at the time of origination), their ex-post performance is actually *better* than similar loans held by the lender (similar to Ambrose et al., 2009). They attribute this difference to the use of post-origination information by investors deciding whether or not to allow individual loans into securitized pools.

As with Jiang et al. (2014), we also find evidence that postorigination selection may have improved the performance of the pool of securitized loans. However, their results are obtained for a single lender that specialized in relatively risky lending in a restricted geographic area and was placed into conservatorship by the FDIC in mid-2008. By contrast, our data set is representative of the entire mortgage market, most of which were actually safer prime loans. And indeed, the results we obtain for prime mortgages are different: We find that these securitized loans perform worse, even ex post.

3. DATA DESCRIPTION

We use loan-level data from the LPS data set. These data have been used to study the determinants of mortgage default (Elul et al., 2010) and to examine foreclosure outcomes (Piskorski, Seru, and Vig, 2010, and Foote et al., 2009). A more detailed description of the data may also be found in Foote el al. (2009). These data are provided by the servicers of the loans, and the contributors include nine of the top 10 servicers.

We focus on first mortgages that originated in 2005 and 2006 since coverage of the LPS data was not as extensive prior to 2005 (particularly for subprime loans), and because by early 2007, the housing market had already showed signs of deterioration. The LPS data cover about 70 percent of all mortgage originations in these years.[6] We impose several additional restrictions in order to create a more homogeneous sample: (i) we restrict attention to owner-occupied homes and exclude multifamily properties; (ii) we consider the three most common maturities: 15, 30, and 40 years; (iii) for adjustable-rate mortgages, we restrict attention to hybrid-ARMs with initial fixed-rate periods of 24, 36, 60, 84, or 120 months; and (iv) to reduce survival bias, we also restrict attention to loans that entered the LPS data set within 12 months of their origination date. This subset represents about 60 percent of all of the first mortgages in the LPS data. Except for prime FRM, where we draw a 50 percent random sample, we used all of the loans available in the LPS data set that met our criteria. We follow our borrowers through April 2009.

We divide our sample into eight distinct subsamples. First, we split it based on whether the loan is prime FRM, prime ARM, subprime FRM, or subprime ARMs. A loan is categorized as prime or subprime based on the servicer's classification; note that there is no separate category for Alt-A loans; depending on the issuer, they may be classified as either prime or subprime. In addition, we also divide the samples further depending on whether the balance at origination is below the conforming loan limit (conforming) or above it (jumbo).[7] The rationale for splitting the data is that the distribution of investor types varies widely across these subsamples (Table 1), as well as loan characteristics (Panels A and B of Table 2); thus, it is possible that the effect of private securitization may vary as well.

Variables

[6] For example, 7.4 million first mortgage originations were recorded in LPS in 2005, compared with 10.5 million in the Home Mortgage Disclosure Act (HMDA) data, and 6.4 million in 2006, compared with 8.6 million in HMDA.

[7] The government-sponsored enterprises (GSEs) are restricted to guaranteeing loans with balances no higher than the conforming loan limit. Such loans are termed "conforming;" loans with balances above this are known as jumbo loans. In 2005, the conforming loan limit for single-family homes was $359,650, and in 2006, it was $417,000.

The LPS data set is divided into a "static" file, with values that generally do not change over time, and a "dynamic" file. The static data set contains information obtained at the time of the original underwriting, such as the loan amount, house price, (origination) FICO score, documentation status (i.e., full-documentation versus low/no documentation of income and assets), the source of the loan (e.g., whether it was broker-originated), property location (zip code), type of loan (fixed-rate, ARM, prime, subprime, IO, Option-ARM, etc.), and whether there is a penalty for prepayment.

The dynamic file is updated monthly, and, among other variables, it contains the status of the loan (current, 30 days delinquent, 60 days, etc.), the current interest rate (since this changes over time for ARMs), current balance, and investor type (private-securitized, Ginnie Mae, Fannie Mae, Freddie Mac, portfolio, FHA). The investor type variable is discussed in greater detail below.

We add in county-level unemployment rates from the Bureau of Labor Statistics and merge house price index data from the Federal Housing Finance Agency (FHFA) (the MSA-level index when available, otherwise the rural or state-level index). Since the house price index is available quarterly, we then follow the mortgages on a quarterly basis as well.

4. METHODOLOGY

We estimate dynamic logit models for mortgage default that are equivalent to discrete duration models.[8] If we find that private-securitized mortgages default at higher rates, after controlling for observable risk characteristics, we will interpret this as support for the adverse selection hypothesis of securitization.

[8] As in Gross and Souleles (2002), we use a fifth-order polynomial in loan age to model the associated hazard function. We also include state, quarter, and origination quarter dummy variables. In a previous version of this paper, we obtained similar baseline results with a Cox proportional hazard model.

Our dependent variable is a dummy variable indicating when a mortgage first becomes 60+ days delinquent (i.e., it is first reported as having missed two or more payments).[9] This is a relatively early definition of default, compared with a foreclosure that can occur many months later. We use this early definition for two reasons. First, state laws governing foreclosure differ widely, and this can have an effect on the length of time it takes to conclude a foreclosure.[10] Also, whether or not a delinquent loan is securitized may also affect the ease of modifying it and hence avoiding foreclosure, i.e., monitoring (Piskorski, Seru, and Vig, 2010, and Agarwal et al., 2011).[11] We further address the issue of monitoring below.

The independent variables include standard mortgage and borrower characteristics from the LPS data set (e.g., the initial loan-to-value ratio (LTV) and origination FICO score), all taken from the time of origination. One exception is the investor type, which is determined at six months following origination, as described below. We also estimate the current LTV, dividing the current mortgage balance (from the LPS data) by an estimate of the current house price. The latter is obtained by updating the house value at origination, using the change in the local house price index since origination. We also compute the change in the county-level unemployment rate over the previous year to capture the effect of shocks.

More precisely, for month t, observed quarterly following mortgage origination (in January, April, July, and October), a default is defined as the homeowner being 60 or more days delinquent for the first time in the following three months: t+1, t+2, or t+3. For example, for month *t* in January, the model would capture the event of a first default in February, March, or April).

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[9] We use the Mortgage Bankers Association (MBA) definition of delinquency: A loan increases its delinquency status if a monthly payment is not received by the end of the day immediately preceding the loan's next payment due date.

[10] Many papers have studied the effect of these state laws on foreclosure outcomes; for example, Ghent and Kudlyak (2011) use the LPS data to address laws that restrict deficiency judgments.

[11] But see Foote et al. (2009) for an opposing view.

The independent variables are all lagged relative to the default event. The LPS mortgage control variables, most notably the first mortgage balance, come from month t. Since their precise timing is unknown, the variables from the other data sets are lagged further: The house price index is the average for the previous quarter, i.e., over months t-3, t-2, and t-1, and the change in the county unemployment rate is taken from months t-13 to t-1.

The Investor Type

The final independent variable that we include in our estimations is the private securitization dummy, which is derived from the investor type. Since this is the key variable in our analysis, we now discuss its construction in more detail. The investor types available in the LPS data set are as follows: portfolio, Ginnie Mae, Fannie Mae, Freddie Mac, and private-securitized. For the purposes of this paper, we combine Fannie Mae and Freddie Mac into a single category: GSE. In addition, mortgages in Ginnie Mae pools are included in the FHA category. These investor types are dynamic and can change every month. In Figure 1, we plot the fraction of loans that change investor type as a function of the time since origination.

The fact that the investor type can change over time is particularly important in determining the "intended" investor type at origination. Because of the time it takes a loan to go through the securitization pipeline, 70 percent of all mortgages are initially recorded as portfolio loans when they first appear in the data set; therefore, simply using the investor type at origination would clearly not capture the intended type. On the other hand, a default can also lead the loan to be transferred to another investor (for example, back to the originating lender in the case of early defaults). For instance, loans for which two payments were missed (our definition of default) are one-third more likely to change investor type than nondefaulting loans.[12] In light of this, we define the "final investor type" to be those reported at six months from loan origination. This is early enough to avoid most defaults (but see our discussion of early defaults that follows) yet far enough from the origination date to reduce the likelihood that the loan is still "in pipeline."[13] Table 1 reports the distribution of loans by final investor type for each product.

5. ESTIMATION AND RESULTS

To motivate our analysis, we begin by plotting nonparametric default hazard functions for both private-securitized and nonprivate-securitized loans (Figure 2). The x-axis gives the mortgage age (in months), and the y-axis gives the probability of default in the next quarter, conditional on not having defaulted before. Notice that private-securitized prime mortgages exhibit significantly higher default risk. For instance, for prime ARMs, the hazard rate of default peaks at 1.5 percent per quarter for private-securitized loans, double the peak for nonprivate-securitized loans. It is also interesting to observe that the impact of securitization is smaller in the subprime market, with nonprivate-securitized subprime ARMs actually defaulting at lower rates early in their lives. As we demonstrate below, this difference is attributable to "early defaults." That is, some of these loans may have been so risky that they defaulted before they could be securitized.

We now study these patterns more formally in a multivariate framework. We will estimate the following model for homeowner i in month t: Pr(default) = Pr ($z<Z_{it}$), where z follows a logistic distribution. As discussed previously, default is defined as the homeowner being delinquent 60 or more days on his mortgage in the subsequent three months, and

[12] The investor type is even more likely to change in later stages of default.

[13] This definition is also used by Bubb and Kaufman (2014). In an earlier version of this paper, we considered a different definition of the investor type and obtained nearly identical estimation results.

$$Z_{it} = X_i^{orig}\beta^{orig} + X_{it}^{current}\beta^{current} + Investor_i\beta^{investor}\ .$$

X^{orig} includes variables defined at origination, such as FICO score, initial LTV, a dummy variable for the origination month, and $X^{current}$ refers to the variables that are updated during the life of the loan, such as time since origination (which enters as a fifth-order polynomial), current LTV, interest rate, current quarter, and the county unemployment rate. Finally, ***Investor***, the key variable of interest, is the investor type six months following loan origination, and takes on the values Portfolio, FHA, GSE, or Private Securitized.

5.1 Baseline Results

Panels A and B in Table 3 report the point estimates, standard errors, and marginal effects for our baseline specification.

Beginning with the prime subsamples in panel A, we first note that the marginal effects for the variables commonly used in mortgage default studies have the expected signs. For example, for prime conforming FRM, broker-originated loans have a 0.22 percentage point per quarter (pp/q) higher risk of default than the omitted category: retail-originated loans. This is a sizable effect, relative to a sample average default rate of about 0.9 pp/q. A borrower with a higher FICO score is less likely to default in all subsamples, while loans with higher interest rates, and loans with higher current LTV are more likely to default. There is no consistent pattern to the effect of initial LTV. This may be understood, however, by noting that we also control for current LTV (using updated balances and house price indexes), and thus, this may reflect the effect of sorting on unobservables (for analogous results, see also Berger and Udell, 1990, who find that riskier commercial loans tend to have more collateral).

We now turn to the key variable of interest, the investor type. For prime mortgages, private-securitized loans are significantly riskier for all subsamples. To gauge the economic significance of this result, observe that for prime conforming FRM, the marginal effect of private securitization is 0.24 pp/q, and for prime conforming ARMs, it is 0.66 pp/q; these are sizable compared with the sample average default rates of 0.9 pp/q and 2.2 pp/q, respectively. The results for prime ARMs are particularly noteworthy in providing support for the hypothesis that lenders used private information to determine which loans to securitize because this segment has significant shares in all of the main sectors: portfolio and private-securitized and for conforming loans, GSE as well (Table 1). Furthermore, retaining ARMs in portfolio entails substantially less interest rate risk for lenders and thus makes cream-skimming less costly. The results for jumbo loans are similar — private-securitized loans are again riskier. We conjecture that the smaller effect, relative to conforming loans, may reflect the reliance of the jumbo market on private securitization (and thus, the risk to the lender of adverse selection), since the GSEs are not permitted to purchase these loans.

With regard to the other investor types, GSE loans are less likely to default than portfolio loans, both for FRMs and ARMs, although the effect is economically small (on the order of 0.06 pp/q). Fixed-rate FHA loans do not appear to be significantly riskier, after controlling for observable characteristics, while FHA ARMs are modestly more likely to default. Note, however, that FHA loans constitute only 1 percent of prime ARMs.

Turning now to the subprime samples, the private securitization coefficients are all negative, in contrast to the results for prime loans, discussed previously. That is, private-securitized loans default at lower rates, *ceteris paribus*. As we demonstrate in the next subsection, this may be attributed to early defaults. That is, some loans may have been so risky that it may not have been possible to securitize them before they defaulted, and thus, they end up being overrepresented in lender portfolios.

5.2 Early Default and Securitization

To understand why private-securitized subprime loans appear to be less risky in our baseline results, it is useful to recall that the vast majority of loans begin as portfolio loans and are only transferred to mortgage-backed securities after a period of several months in the pipeline. Thus, paradoxically, lenders may have intended to sell very risky loans to securitized pools, but they were not able to do so because the mortgages defaulted before they had a chance to do so. Table 2 reports the fraction of loans that became delinquent within six months of origination: For prime loans, this is fairly small, but the proportion is much higher for the subprime subsamples. Furthermore, subprime loans that are held in portfolio are more likely to default early than securitized loans: For example, nearly 34 of subprime conforming ARMs held in portfolio compared with 20 percent of those that were securitized.

To control for this, we rerun our baseline model, but this time, we exclude all loans that exhibited any delinquency within six months of origination (even one month). Estimates of the coefficients and marginal effects for the investor types are reported for each subsample in Table 4. Note that dropping early defaulting mortgages has only a modest effect on the results for prime loans, which is not surprising since only a small fraction of loans fall into this category. The impact on subprime loans is much more dramatic, however. Observe that the securitization coefficients are no longer significantly negative, and for conforming adjustable-rate subprime mortgages, dropping early defaulting loans results in private-securitized loans that are significantly riskier. Thus, as in Jiang et al. (2010), we find that postorigination selection may have improved the performance of the pool of securitized loans.

Given the important role played by early default in the subprime market, for the remainder of the paper, we restrict all estimations involving the subprime samples to mortgages for which no payments were missed during the first six months following origination. We do not impose this restriction on the prime subsamples, although the results would have been little changed had we done so.

5.3 Documentation Type

Keys et al. (2009) found that the extra default risk for subprime securitized loans is concentrated in those with low or no documentation. They argue that these results support the existence of adverse selection because low documentation loans are precisely those for which the asymmetry of information is greatest. That is, given the paucity of verified "hard" information for these borrowers, lenders may well have collected additional "soft" information, which was not shared with investors.

We generalize their results to the broader set of data that we have available to us. To simplify the model, we drop the GSE and FHA investor types and keep only portfolio and private-securitized loans. We then interact the investor type with a dummy variable for whether or not the loan has full documentation. In Table 5, we report the marginal effects of private securitization on default risk, both for the full sample as well as separately for full and low-/no-documentation loans.

We first observe that our results confirm those of Keys et al. (2009): For conforming subprime ARMs, we find that private securitization is associated with significantly higher default risk for low-/no-documentation loans but not for full documentation loans. However, we do not find any significant difference for any of our other subsamples. These results suggest that further research should be undertaken to determine the extent to which the finding by Keys et al. (2009) is a general one.

5.4 Robustness

We also extend our analysis in several directions to confirm the robustness of our results.

Lender Fixed Effects

One of the limitations of the LPS data set is that it does not include information on the lender's identity. This is information that investors could have observed since it was available from the prospectus and other data sets such as Loan Performance. Thus, its absence opens the door to the possibility that the effect of private securitization can be attributed to a few lenders who were known to originate riskier loans, something that investors could have taken into account. That is, lender reputation may have mitigated the effect of adverse selection.

In order to address this concern, we merge our LPS data with the Home Mortgage Disclosure Act (HMDA) data.[14] This gives us an anonymous identifier for each lender, which allows us to rerun our earlier estimations with lender fixed effects.[15] For tractability, we further restrict attention to loans originated by the top-25 lenders in each subsample; this leaves us with approximately 50 percent of the original data for the prime subsamples and 25 percent for the subprime subsamples.

The point estimates and marginal effects for the investor types are reported in Table 6. Broadly speaking, the results are similar to those we have already established earlier. Aside from prime jumbo FRM, private-securitized loans remain riskier for all of the prime subsamples. For subprime loans, it is again the case (as in Table 4) that private securitization is not associated with lower default risk once we drop early defaulting loans. However, we observe more differences, perhaps due to the smaller sample size: Conforming subprime FRMs are now significantly riskier, whereas this is no longer the case for conforming subprime ARMs.

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[14] Our procedure is similar to that described in Haughwout, Mayer, and Tracy (2009). Mortgages were matched based on the zip code of the property, the date when the mortgage originated (within five days), the origination amount (within $500), the purpose of the loan (purchase, refinance, or other), the type of loan (conventional, VA guaranteed, FHA guaranteed, or other), occupancy type (owner-occupied or nonowner-occupied), and lien status (first lien or other). The match rate was approximately 50 percent.

[15] The anonymity is due to restrictions imposed by the data provider.

CBSA Fixed Effects

In addition, since there may be heterogeneity across borrowers within a state, we also replace the state fixed effects with dummy variables for each CBSA and rerun our analysis. To make the analysis tractable, we restrict attention to the 250 largest CBSAs; as can be seen from Table 2, this excludes fewer than 20 percent of the loans for each subsample. The results, reported in Table 7, are very similar to those we have already established.

Effect of Securitization over Time

The time period we study is one of dramatic changes in the mortgage market. It is interesting to consider how the relationship between private securitization and default risk may have changed over time. In Table 8, we report the results from dividing our sample into three time periods: 2005Q1-2006Q4, 2007Q1-2008Q1, and 2008Q2-2009Q2, and then, estimating our model separately over each time period. Generally speaking, for the prime subsamples, the relationship between private securitization and default risk is strongest in the later time periods: In 2005–2006, there is either a negative relationship (for FRMs) or a fairly weak positive relationship (ARMs). One explanation for the evolution of this relationship over time may be that the relationship between private securitization and default risk did not become apparent until dramatic drops in house prices made default more attractive for a larger class of homeowners.

As we have already noted, for our subprime samples, the relationship between private securitization and default is the strongest for subprime conforming ARMs. We see that this relationship is concentrated both in the earliest and the latest time periods. In addition, for subprime conforming FRMs, while pooling all the time periods together in the same model yielded an insignificant relationship (Table 4), Table 8 shows that this is due to the later time periods: The early time periods show a significantly positive relationship.

Propensity Score Matching

In Table 2, we see that there are some differences in loan characteristics across the investor types within subsamples, which may also be correlated with default risk. For example, privately securitized prime fixed-rate conforming loans are more likely to be interest-only, as compared with other investor types. As a result, we conduct a propensity score matching analysis, along the lines of Agarwal et al. (2012). For each subsample, we match a securitized loan with a similar portfolio loan, based on characteristics at origination.[16] We then rerun our logit analysis on this sample of matched loans. Although this reduces the sample size significantly, it has the advantage of creating a more uniform set of observations. The results are reported in Table 9. The results are qualitatively similar to those reported earlier: Prime private-securitized loans continue to be riskier than portfolio loans (aside from jumbo FRMs, where the difference is insignificant), and we find no significant difference for subprime loans.

[16] In particular, the variables used in this first stage are interest rate, FICO score, loan source, initial LTV, refinancing, property type, loan size, documentation type, interest-only flag, and origination year. We keep only those matched pairs with a propensity score above 0.5. We drop FHA loans and conduct the analysis separately for GSE-securitized and private-securitized loans.

6. CONCLUSIONS

Using a large data set that includes information on both securitized and nonsecuritized mortgages, we have demonstrated robust evidence that private-securitized loans originated during 2005–2006 were riskier than comparable nonsecuritized loans. These results are consistent with the existence of adverse selection between lenders and investors. For subprime mortgages, this effect is concentrated in loans with low or no documentation of income and assets, although prime private-securitized mortgages are riskier overall (although the effect is stronger for low-/no-documentation loans). These results are economically important, as prime loans made up the vast majority of the mortgage market.

More work is needed to examine whether investors priced the extra risk of these loans fairly, which is something that our data do not allow us to fully address. It is also important to further investigate the private information that lenders might have used to screen these loans.

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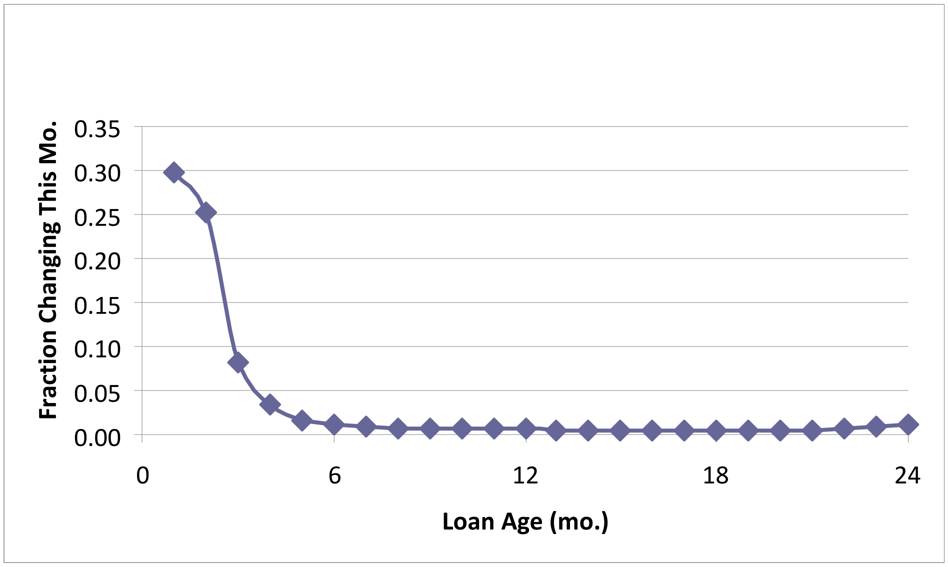

Figure 1. Evolution of Investor Type over Time
We plot the fraction of mortgages whose investor type, as reported in the LPS data set, changed from the previous month, as a function of the time since loan origination.

Table 1. Investor Type at Six Months
The share of mortgages, by investor type at six months following origination, for each subsample

	Prime FRM		**Prime ARM**		**Subprime FRM**		**Subprime ARM**	
	Conforming	Jumbo	Conforming	Jumbo	Conforming	Jumbo	Conforming	Jumbo
Portfolio	0.05	0.08	0.14	0.36	0.03	0.03	0.09	
FHA/VA	0.10		0.01					
GSE	0.74		0.51		0.17			
Private Securitized	0.12	0.92	0.33	0.64	0.80	0.97	0.91	

Table 2: Panel A. Summary Statistics: Prime Mortgages
This table reports summary statistics, by investor type at six months following origination, for prime mortgages in our sample. Default rate, loan age, current LTV, interest rate, unemployment change are computed as average over entire sample. All other variables are at time of origination.

	Prime FRM - Conforming				Prime FRM - Jumbo		Prime ARM - Conforming				Prime ARM - Jumbo	
	Portfolio	FHA	GSE	Priv Securit	Portfolio	Priv Securit	Portfolio	FHA	GSE	Priv Securit	Portfolio	Priv Securit
FICO orig	707	651	719	705	736	732	727	653	728	717	735.8232	727.1554
ln(loan amt)	11.913	11.759	11.972	11.992	13.305	13.222	12.310	11.959	12.253	12.284	13.32454	13.27296
Initial LTV	0.758	0.947	0.706	0.716	0.705	0.703	0.714	0.960	0.715	0.747	0.70587	0.725851
LTV=80%	0.085	0.001	0.132	0.176	0.144	0.197	0.190	0.000	0.184	0.247	0.214661	0.259771
IO	0.006	0.000	0.014	0.098	0.027	0.139	0.678	0.000	0.535	0.808	0.76521	0.79162
OptionaARM							0.326	0.000	0.137	0.022	0.167449	0.144352
Refi	0.397	0.194	0.493	0.479	0.440	0.480	0.447	0.085	0.403	0.334	0.439369	0.383809
Cashout Refi	0.228	0.063	0.244	0.286	0.206	0.208	0.209	0.003	0.189	0.161	0.101998	0.158848
Prep. Pnlty	0.051	0.000	0.004	0.091	0.028	0.055	0.057	0.000	0.035	0.206	0.045569	0.0946
Corresp.	0.070	0.371	0.335	0.224	0.091	0.275	0.121	0.116	0.199	0.166	0.153814	0.111287
Broker	0.348	0.120	0.155	0.155	0.182	0.156	0.277	0.037	0.180	0.127	0.235877	0.186027
Lowdoc	0.057	0.190	0.178	0.137	0.071	0.111	0.310	0.050	0.248	0.171	0.297361	0.183869
Condo	0.155	0.075	0.117	0.122	0.095	0.082	0.247	0.223	0.251	0.290	0.138757	0.145877
Early Default	0.062	0.085	0.036	0.063	0.047	0.042	0.041	0.081	0.032	0.046	0.042945	0.057237
Term												
15 yr	0.086	0.024	0.122	0.064	0.109	0.063	0.001	0.000	0.000	0.000	0.000	0.000
30-yr	0.856	0.976	0.875	0.923	0.829	0.933	0.983	1.000	0.996	0.996	0.996474	0.998049
40-yr	0.059		0.002	0.012	0.063	0.005	0.016	0.000	0.004	0.004	0.003287	0.001855
ARM Fxd. Prd.												
24							0.014	0.020	0.000	0.072	0.004	0.084
36							0.097	0.823	0.075	0.083	0.064806	0.051828
60							0.587	0.153	0.574	0.507	0.577393	0.474194
84							0.201	0.003	0.207	0.152	0.129567	0.148246
120							0.101	0.002	0.144	0.187	0.224514	0.241776
2006 orig	0.622	0.525	0.484	0.441	0.459	0.413	0.412	0.434	0.429	0.396	0.356608	0.459308
Top 25 lende	0.568	0.432	0.421	0.285	0.626	0.388	0.595	0.757	0.525	0.447	0.497062	0.534498
Top 250 CBSA	0.921	0.805	0.880	0.898	0.979	0.976	0.959	0.874	0.947	0.956	0.986751	0.986064
Default	0.011	0.019	0.007	0.015	0.006	0.008	0.013	0.019	0.096	0.050	0.007998	0.017753
Age	18.451	18.558	19.224	18.797	19.627	20.143	19.268	17.968	18.850	17.260	19.975	18.83486
Current LTV	0.711	0.873	0.646	0.661	0.656	0.651	0.681	0.885	0.670	0.729	0.667268	0.691633
Int Rate (%)	6.091	6.119	6.073	6.397	5.989	6.099	5.854	5.235	5.728	6.780	5.67228	5.883969
Unemp Chang	0.440	0.268	0.386	0.357	0.487	0.465	0.391	0.180	0.363	0.275	0.433997	0.436262
# loans	90255	181506	1394284	230088	8968	106790	30819	2657	136202	36962	113169	217780

Table 2: Panel B. Summary Statistics: Subprime Mortgages

This table reports summary statistics, by investor type at six months following origination, for subprime mortgages in our sample. Default rate, loan age, current LTV, interest rate, unemployment change are computed as average over entire sample. All other variables are at time of origination.

	Subprime FRM - Conforming			Subprime FRM - Jumbo		Subprime ARM - Conforming		Subprime ARM - Jumbo	
	Portfolio	GSE	Priv Securit	Portfolio	Priv Securit	Portfolio	Priv Securit	Portfolio	Priv Securit
FICO orig	613	597	608	645	643	605	608	631	630
ln(loan amt)	11.696	11.676	11.857	13.087	13.112	11.916	11.915	13.077	13.083
Initial LTV	0.717	0.791	0.764	0.777	0.776	0.804	0.804	0.809	0.809
LTV=80%	0.196	0.120	0.185	0.261	0.205	0.301	0.246	0.420	0.345
IO	0.003	0.000	0.039	0.023	0.121	0.055	0.160	0.118	0.322
OptionaARM	0.604	0.645	0.750	0.700	0.772	0.664	0.221	0.812	0.385
Refi	0.327	0.561	0.610	0.468	0.679	0.417	0.472	0.416	0.492
Cashout Refi	0.768	0.000	0.768	0.858	0.815	0.243	0.347	0.315	0.409
Prep. Pnlty	0.136	0.605	0.124	0.115	0.067	0.763	0.790	0.761	0.799
Corresp.	0.268	0.054	0.199	0.343	0.269	0.120	0.142	0.123	0.107
Broker	0.060	0.149	0.030	0.105	0.035	0.473	0.317	0.605	0.439
Lowdoc	0.083	0.059	0.065	0.094	0.056	0.197	0.126	0.392	0.255
Condo	-0.427	-0.398	-0.413	-0.521	-0.440	0.135	0.105	0.134	0.101
Early Default	0.263	0.174	0.173	0.209	0.151	0.338	0.204	0.334	0.200
Term									
15-yr	0.069	0.049	0.047			0.000	0.000	0.000	0.000
30-yr	0.854	0.949	0.840	0.772	0.815	0.822	0.911	0.602	0.782
40-yr	0.077	0.002	0.113	0.205	0.172	0.178	0.089	0.398	0.218
ARM Fxd. Prd.									
24						0.871	0.775	0.000	0.000
36						0.117	0.204	0.094	0.155
60						0.012	0.021	0.015	0.035
84						0.000	0.000	0.000	0.000
120						0.000	0.000	0.000	0.000
2006 orig	0.472	0.562	0.623	0.423	0.598	0.256	0.395	0.228	0.307
Top 25 lender	0.264	0.294	0.357	0.275	0.426	0.251	0.347	0.185	0.320
Top 250 CBSA	0.881	0.817	0.890	0.977	0.983	0.909	0.905	0.987	0.986
Default	0.055	0.046	0.055	0.053	0.059	0.091	0.074	0.116	0.091
Age	18.659	15.552	16.260	19.004	17.066	13.867	13.645	12.500	13.093
Current LTV	0.659	0.752	0.721	0.720	0.746	0.737	0.754	0.746	0.754
Int Rate (%)	7.906	7.326	7.844	6.861	6.780	7.796	7.995	7.215	7.266
Unemp Change (1-yr;%)	0.213	0.214	0.288	0.318	0.467	-0.142	-0.052	-0.216	-0.103
# loans	9400	43036	207645	487	14681	43442	466560	5675	47579

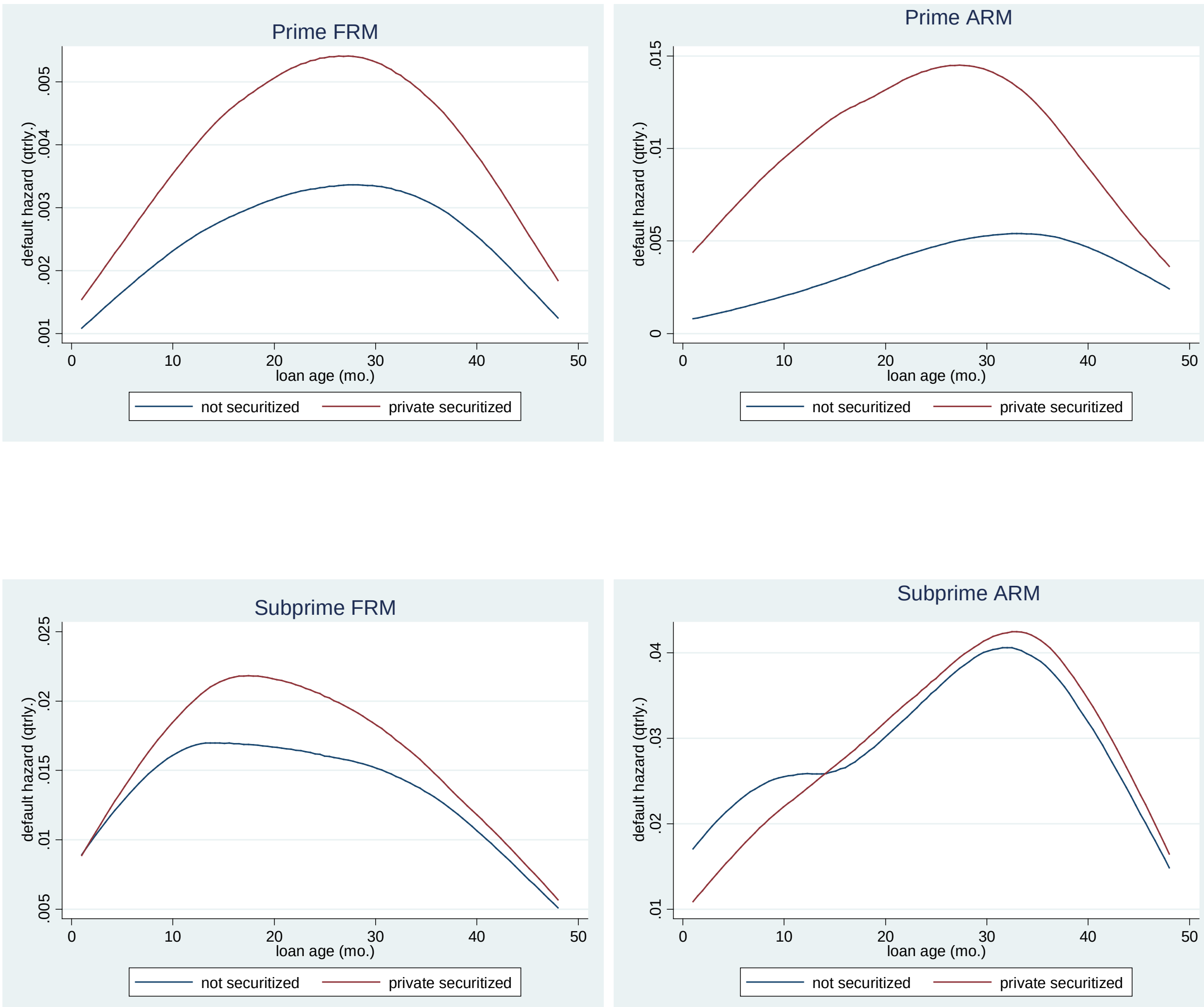

Figure 2. Nonparametric default hazard functions. This figure plots the hazard of default, breaking down the sample by private and nonprivate-securitized loans, as a function of the time since origination. Conforming and jumbo loans are combined. Default is defined as the first time a loan is 60 or more days delinquent in the next three months.

Table 3: Panel A. Dynamic Model of Mortgage Default: Prime Mortgages
This panel reports the results from an estimating dynamic logit model of default on the investor type at six months following origination, as well as other covariates, for prime mortgage subsamples. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Baseline categories: 30-year term, 2/28 ARM, single-family property, full-documentation, portfolio loan, purchase loans.

	Prime FRM								Prime ARM							
	Conforming				Jumbo				Conforming				Jumbo			
	Coef	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)
FHA	-0.002	(0.014)		-0.002%					0.145	(0.030)	**	0.259%				
GSE	-0.075	(0.013)	**	-0.065%					-0.036	(0.010)	**	-0.060%				
Priv. Securit.	0.237	(0.014)	**	0.238%	0.127	(0.052)	**	0.092%	0.321	(0.010)	**	0.619%	0.288	(0.012)	**	0.362%
Int. Rate	0.488	(0.005)	**	0.435%	1.084	(0.027)	**	0.827%	0.345	(0.004)	**	0.661%	0.654	(0.010)	**	0.869%
Current LTV	2.278	(0.027)	**	2.028%	1.456	(0.120)	**	1.111%	2.425	(0.033)	**	4.652%	2.293	(0.060)	**	3.046%
Δunemp	0.088	(0.004)	**	0.078%	0.130	(0.022)	**	0.099%	0.124	(0.006)	**	0.239%	0.124	(0.011)	**	0.164%
FICO @orig	0.017	(0.001)	**	-0.011%	0.066	(0.007)	**	-0.008%	0.027	(0.001)	**	-0.015%	0.059	(0.003)	**	-0.012%
$FICO^2$	0.000	(0.000)	**		0.000	(0.000)	**		0.000	(0.000)	**		0.000	(0.000)	**	
Term: 15-yr	-0.197	(0.013)	**	-0.161%	0.049	(0.075)		0.038%	-0.131	(0.220)		-0.237%	0.448	(0.506)		0.720%
Term: 40-yr	0.181	(0.023)	**	0.176%	0.475	(0.074)	**	0.447%	0.128	(0.031)	**	0.259%	0.051	(0.077)		0.069%
Broker	0.229	(0.007)	**	0.220%	0.127	(0.029)	**	-0.020%	0.104	(0.009)	**	0.205%	0.097	(0.014)	**	0.132%
Corresp.	0.091	(0.006)	**	0.082%	-0.183	(0.028)	**	0.100%	-0.127	(0.010)	**	-0.233%	-0.109	(0.017)	**	-0.140%
LTV=80%	0.073	(0.008)	**	0.067%	0.149	(0.026)	**	-0.134%	0.189	(0.006)	**	0.374%	0.199	(0.012)	**	0.272%
Initial LTV	-6.244	(0.370)	**	-0.006%	4.189	(4.346)		0.117%	0.740	(0.842)		-0.659%	-0.732	(2.645)		0.425%
Initial LTV^2	9.896	(0.587)	**		-2.092	(6.335)			2.588	(1.174)	**		8.024	(3.626)	**	
Initial LTV^3	-4.788	(0.294)	**		0.370	(3.023)			-2.711	(0.532)	**		-6.269	(1.624)	**	
Refi	-0.055	(0.007)	**	-0.049%	0.000	(0.027)		1.265%	-0.193	(0.007)	**	-0.362%	-0.074	(0.013)	**	-0.098%
Cashout Refi	0.053	(0.008)	**	0.047%	-0.075	(0.031)	**	0.000%	-0.009	(0.011)		-0.017%	-0.074	(0.018)	**	-0.096%
Condo	-0.096	(0.008)	**	-0.082%	-0.229	(0.042)	**	-0.057%	-0.195	(0.007)	**	-0.357%	-0.268	(0.016)	**	-0.329%
ln(loan amt)	0.049	(0.006)	**	0.044%	-0.315	(0.045)	**	-0.160%	0.245	(0.008)	**	0.470%	-0.135	(0.019)	**	-0.179%
Low/No-Doc	0.000	(0.006)		0.000%	-0.027	(0.034)		-0.241%	0.004	(0.008)		0.008%	0.013	(0.015)		0.018%
Int. Only	0.226	(0.015)	**	0.946%	0.774	(0.027)	**	0.724%	0.188	(0.007)	**	0.360%	0.226	(0.015)	**	0.283%
Prep. Pntly.	0.360	(0.015)	**	0.162%	0.395	(0.039)	**	0.350%	0.193	(0.008)	**	0.391%	0.360	(0.015)	**	0.536%
OptionARM									-0.110	(0.013)	**	-0.202%	-0.155	(0.019)	**	-0.196%
Initial ARM Prd.																
36 mo.									-0.126	(0.011)	**	-0.320%	-0.173	(0.027)	**	-0.439%
60 mo.									-0.524	(0.010)	**	-1.131%	-0.789	(0.024)	**	-1.576%
84 mo.									-0.792	(0.014)	**	-1.540%	-1.102	(0.026)	**	-1.958%
120 mo.									-1.031	(0.015)	**	-1.829%	-1.487	(0.026)	**	-2.302%
N		19370541				1230034				7703392				3333236		

All regressions include quintic polynomial in loan age and fixed effects for state, time, and origination month.
'Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 3: Panel B. Dynamic Model of Mortgage Default: Subprime Mortgages
This panel reports the results from estimating a dynamic logit model of default on the investor type at six months following origination, as well as other covariates, for subprime mortgage subsamples. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Baseline categories: 30-year term, 2/28 ARM, single-family property, full-documentation, portfolio loan, purchase loans.

	Subprime FRM								Subprime ARM							
	Conforming				Jumbo				Conforming				Jumbo			
	Coef	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)
GSE	-0.232	(0.024)	**	-1.291%												
Priv. Securit.	-0.251	(0.019)	**	-1.384%	-0.174	(0.083)	**	-0.965%	-0.326	(0.009)	**	-2.463%	-0.360	(0.025)	**	-3.169%
Int. Rate	0.256	(0.004)	**	1.288%	0.467	(0.019)	**	2.440%	0.234	(0.002)	**	1.588%	0.288	(0.008)	**	2.288%
Current LTV	2.095	(0.047)	**	10.521%	0.950	(0.195)	**	4.962%	2.574	(0.038)	**	17.454%	1.577	(0.124)	**	12.519%
Δunemp	0.044	(0.006)	**	0.222%	0.118	(0.031)	**	0.618%	0.088	(0.004)	**	0.596%	0.159	(0.017)	**	1.266%
FICO @orig	0.001	(0.001)		-0.029%	0.028	(0.004)	**	-0.024%	-0.003	(0.001)	**	-0.028%	0.000	(0.002)		-0.020%
FICO^2	0.000	(0.000)	**		0.000	(0.000)	**		0.000	(0.000)	**		0.000	(0.000)		
Term: 15-yr	-0.262	(0.020)	**	-1.156%	-0.371	(0.160)	**	-1.606%	0.425	(0.341)		3.400%				
Term: 40-yr	0.362	(0.011)	**	2.068%	0.360	(0.038)	**	2.058%	0.026	(0.008)	**	0.175%	0.036	(0.020)	*	0.287%
Broker	-0.069	(0.009)	**	-0.340%	-0.192	(0.034)	**	-0.970%	0.141	(0.006)	**	0.970%	0.104	(0.020)	**	0.829%
Corresp.	-0.077	(0.010)	**	-0.377%	-0.282	(0.055)	**	-1.348%	0.028	(0.007)	**	0.190%	0.037	(0.025)		0.296%
LTV=80%	0.185	(0.009)	**	0.974%	0.355	(0.035)	**	2.002%	0.150	(0.005)	**	1.044%	0.307	(0.016)	**	2.511%
Initial LTV	-8.713	(0.460)	**	-6.571%	- 12.644	(4.172)	**	3.453%	-9.427	(0.515)	**	- 13.935%	-6.917	(3.167)	**	-1.539%
Initial LTV^2	13.486	(0.774)	**		22.528	(6.207)	**		16.042	(0.791)	**		13.160	(4.444)	**	
Initial LTV^3	-7.197	(0.407)	**		- 11.662	(3.018)	**		-9.284	(0.390)	**		-7.328	(2.051)	**	
Refi	-0.515	(0.012)	**	-2.858%	-0.502	(0.054)	**	-2.916%	-0.360	(0.008)	**	-2.411%	-0.340	(0.027)	**	-2.683%
Cashout Refi	0.095	(0.011)	**	0.477%	0.082	(0.049)	*	0.425%	0.128	(0.008)	**	0.888%	0.146	(0.027)	**	1.172%
Condo	-0.072	(0.014)	**	-0.353%	-0.177	(0.063)	**	-0.870%	-0.132	(0.007)	**	-0.858%	-0.056	(0.022)	**	-0.436%
ln(loan amt)	0.333	(0.009)	**	1.674%	0.004	(0.075)		0.023%	0.302	(0.006)	**	2.051%	-0.003	(0.034)		-0.026%
Low/No-Doc	0.141	(0.016)	**	0.744%	0.138	(0.075)	*	0.757%	0.232	(0.007)	**	1.677%	0.169	(0.018)	**	1.375%
Int. Only	0.592	(0.016)	**	3.733%	0.586	(0.045)	**	3.617%	0.081	(0.007)	**	0.564%	0.040	(0.018)	**	0.319%
Prep. Pntly.	-0.086	0.011	**	-0.438%	-0.057	(0.046)		-0.304%	-0.112	(0.008)	**	-0.783%	-0.161	(0.024)	**	-1.330%
OptionARM									-0.030	(0.007)	**	-0.204%	-0.018	(0.023)		-0.146%
Initial ARM Prd.																
36 mo.									-0.037	(0.006)	**	-0.247%	-0.134	(0.020)	**	-1.042%
60 mo.									-0.208	(0.016)	**	-1.312%	-0.462	(0.037)	**	-3.194%
84 mo.									-1.398	(1.265)		-5.627%	-0.422	(0.232)	*	-2.964%
120 mo.									-0.271	(0.185)		-1.670%	-0.557	(0.619)		-3.723%
N	1850382				114417				3142852				311755			

All regressions include quintic polynomial in loan age and fixed effects for state, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 4. No Early Default
This table reports the effect of investor type at six months following origination, in a dynamic logit model of default, in which loans that default within six months following origination are dropped. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Other coefficients are as in Table 3 and are not reported.

	Prime FRM						Prime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
FHA	0.073	(0.016)**	0.050%				0.183	(0.036)**	0.254%			
GSE	-0.009	(0.014)	-0.006%				0.039	(0.011)**	0.051%			
Priv Securit.	0.303	(0.016)**	0.235%	0.276	(0.057)**	0.162%	0.360	(0.011)**	0.542%	0.321	(0.013)**	0.350%
N	18803363			1180087			7374571			3180052		

	Subprime FRM						Subprime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
GSE	0.016	(0.030)	0.055%									
Priv Securit.	0.035	(0.024)	0.127%	0.078	(0.101)	0.317%	0.074	(0.012)**	0.346%	-0.002	(0.030)	-0.013%
N	1667835			104626			2781177			272549		

All regressions include quintic polynomial in loan age and fixed effects for C, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 5. Interaction of Private Securitization and Documentation Type
The table reports the marginal effect of private securitization in a dynamic logit model of mortgage default in which the indicator for private securitization is interacted with the documentation type. The sample is restricted to portfolio and private-securitized mortgages. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Subprime samples (only) are restricted to loans that did not miss any payments in first six months from the loan origination. Other coefficients are as in Table 3 and are not reported.

	Prime FRM						**Prime ARM**					
	Conforming			**Jumbo**			**Conforming**			**Jumbo**		
	Mrg. (%)	**SE**		**Mrg/ (%)**	**SE**		**Mrg. (%)**	**SE**		**Mrg. (%)**	**SE**	
Full Sample	0.231%	(0.061%)	**	0.084%	(0.044%)	*	1.048%	0.331%	**	0.362%	(0.146%)	**
Full-Doc	0.346%	(0.090%)	**	0.110%	(0.049%)	**	1.039%	0.328%	**	0.358%	(0.145%)	**
Low/No-Doc	-0.815%	(0.223%)	**	-0.111%	(0.140%)		1.110%	0.354%	**	0.376%	(0.154%)	**
N	2886468			1230034			3200158			3333236		

	Subprime FRM						**Subprime ARM**					
	Conforming			**Jumbo**			**Conforming**			**Jumbo**		
	Mrg. (%)	**SE**		**Mrg. (%)**	**SE**		**Mrg. (%)**	**SE**		**Mrg. (%)**	**SE**	
Full Sample	0.144%	0.124%		0.285%	(0.417%)		0.297%	0.147%	**	-0.071%	(0.189%)	
Full-Doc	0.137%	0.123%		0.267%	(0.428%)		0.183%	0.106%	*	-0.232%	(0.235%)	
Low/No-Doc	0.355%	0.444%		0.793%	(1.353%)		0.959%	0.452%	**	0.356%	(0.308%)	
N	1397406			104626			2781177			272549		

All regressions include quintic polynomial in loan age and fixed effects for state, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 6. Lender Fixed Effects

This table reports the effect of investor type at six months following origination on mortgage default. It re-estimates the dynamic logit model of mortgage default in Table 3, and adds lender fixed effects. The sample is restricted to loans that were matched to HMDA for the 25 largest lenders. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Subprime samples (only) are restricted to loans that did not miss any payments in first six months from the loan origination. Other coefficients are as in Table 3 and are not reported.

	Prime FRM						Prime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
FHA	-0.168	(0.022) **	-0.139%				0.248	(0.041) **	0.400%			
GSE	-0.200	(0.020) **	-0.162%				-0.015	(0.017)	-0.022%			
Priv Securit.	0.150	(0.023) **	0.144%	-0.114	(0.077)	-0.073%	0.196	(0.020) **	0.310%	0.096	(0.021) **	0.104%
N	8257643			532734			3831862			1790363		

	Subprime FRM						Subprime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
GSE	0.182	(0.063) **	0.587%									
Priv Securit.	0.191	(0.053) **	0.620%	0.174	(0.214)	0.697%	0.025	(0.028)	0.116%	-0.078	(0.082)	-0.496%
N	585968			44893			971427			85500		

All regressions include quintic polynomial in loan age and fixed effects for state, time, origination month, and lender. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 7. CBSA Fixed Effects

This table reports the effect of investor type at six months following origination on mortgage default, reestimating the dynamic logit model of mortgage default models in Table 3, and replacing the state fixed effects with CBSA fixed effects. The sample is restricted to properties in the 250 largest CBSAs. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Subprime samples (only) are restricted to loans that did not miss any payments in first six months from the loan origination. Other coefficients are as in Table 3 and are not reported.

	Prime FRM						Prime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
FHA	0.024	(0.015)	0.021%				0.140	(0.033) **	0.251%			
GSE	-0.066	(0.013) **	-0.056%				-0.038	(0.010) **	-0.063%			
Priv Securit.	0.246	(0.015) **	0.243%	0.109	(0.053) **	0.080%	0.311	(0.010) **	0.599%	0.279	(0.012) **	0.352%
N	1.6E+07			1182592			7108629			3258325		

	Subprime FRM						Subprime ARM					
	Conforming			Jumbo			Conforming			Jumbo		
	Coef	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)	Coef.	SE	Mrg. (%)
GSE	-0.012	(0.033)	-0.043%									
Priv Securit.	0.014	(0.026)	0.051%	0.104	(0.105)	0.424%	0.072	(0.013) **	0.351%	-0.004	(0.030)	-0.027%
N	1359586			100806			2319297			265589		

All regressions include quintic polynomial in loan age and fixed effects for CBSA, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 8. Effect of Securitization by Time Period
This table reports the effect of investor type at six months following origination on mortgage default, reestimating the dynamic logit model of mortgage default models in Table 3, for three distinct time periods: 2005Q1-2006Q4, 2007Q1-2008Q1, 2008Q2-2009Q2. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Subprime samples (only) are restricted to loans that did not miss any payments in first six months from the loan origination. Other coefficients are as in Table 3 and are not reported.

		Prime FRM								Prime ARM							
		Conforming				Jumbo				Conforming				Jumbo			
		Coef	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)
200501-200612	FHA	-0.319	(0.029)	**	-0.215%					0.337	(0.057)	**	0.401%				
	GSE	-0.475	(0.028)	**	-0.299%					-0.174	(0.028)	**	-0.167%				
	Priv. Securit	-0.180	(0.032)	**	-0.129%	-0.527	(0.115)	**	0.080%	0.174	(0.030)	**	0.192%	0.197	(0.039)	**	0.103%
	N	6251447				397541				2788259				1165305			
200701-200801	FHA	0.058	(0.022)	**	0.046%					0.192	(0.047)	**	0.347%				
	GSE	0.012	(0.020)		0.009%					-0.113	(0.016)	**	-0.178%				
	Priv. Securit	0.357	(0.022)	**	0.327%	0.172	(0.091)	*	0.106%	0.352	(0.016)	**	0.683%	0.368	(0.022)	**	0.416%
	N	7878191				484887				3099086				1307804			
200804-200904	FHA	-0.008	(0.021)		-0.012%					-0.039	(0.055)		-0.110%				
	GSE	-0.051	(0.018)	**	-0.069%					0.006	(0.014)		0.018%				
	Priv. Securit	0.265	(0.020)	**	0.416%	0.271	(0.068)	**	0.363%	0.265	(0.014)	**	0.856%	0.241	(0.016)	**	0.597%
	N	5240903				345739				1816047				858815			

		Subprime FRM								Subprime ARM							
		Conforming				Jumbo				Conforming				Jumbo			
		Coef	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)	Coef.	SE		Mrg. (%)
200501-200612	GSE	0.194	(0.079)	**	0.27%												
	Priv. Securit	0.125	(0.062)	**	0.17%	0.042	(0.225)		0.06%	0.119	(0.022)	**	0.25%	0.001	(0.067)		0.00%
	N	518347				27667				1410487				124102			
200701-200801	GSE	0.099	(0.044)	**	0.38%												
	Priv. Securit	0.049	(0.036)		0.18%	0.183	(0.161)		0.71%	0.026	(0.017)		0.16%	-0.024	(0.037)		-0.20%
	N	747514				47588				1026352				121860			
200804-200904	GSE	-0.143	(0.047)	**	-0.86%												
	Priv. Securit	-0.02	(0.038)		-0.13%	0.117	(0.171)		0.53%	0.084	(0.024)	**	0.89%	0.067	(0.068)		0.97%
	N	398007				27048				337638				26531			

All regressions include quintic polynomial in loan age and fixed effects for state, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.

Table 9. Matched Samples
This table reports the effect of securitization on mortgage default, in the dynamic logit model of Table 3, for subsamples that were generated through propensity score matching of securitized loans with portfolio loans, based on origination characteristics. The effect of private securitization and GSE securitization, relative to portfolio loans, estimated separately; FHA loans were dropped. The dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Subprime samples (only) are restricted to loans that did not miss any payments in first six months following loan origination. Other coefficients are as in Table 3 and are not reported.

	Prime FRM										**Prime ARM**									
	Conforming					**Jumbo**					**Conforming**					**Jumbo**				
	Coef	**SE**		**Mrg.(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**
Priv. Securit.	0.125	(0.022)	**	0.144%	1135090	0.087	(0.090)		0.043%	186046	0.227	(0.014)	**	0.458%	1434319	0.153	(0.017)	**	0.138%	1960231
GSE	-0.057	(0.018)	**	-0.075%	1666495						0.109	(0.014)	**	0.140%	2272500					

	Subprime FRM										**Subprime ARM**									
	Conforming					**Jumbo**					**Conforming**					**Jumbo**				
	Coef	**SE**		**Mrg.(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**	**Coef.**	**SE**		**Mrg(%)**	**N**
Priv. Securit.	-0.170	(0.045)	**	-0.474%	133704	0.069	(0.239)		0.219%	6889	0.045	(0.017)	**	0.213%	437528	0.048	(0.042)		0.304%	51905
GSE	0.111	(0.101)		0.299%	72077															

All regressions include quintic polynomial in loan ageand fixed effects for state, time, and origination month. Standard errors are reported in parentheses and are clustered at the loan level. The ** and * indicate significance at the 5% and 10% levels, respectively.