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ABSTRACT

The academic literature, the popular press, and policymakers have all debated securitization's contribution to the poor performance of mortgages originated in the run-up to the recent crisis. Theoretical arguments have been advanced on both sides, but the lack of suitable data has made it difficult to assess them empirically. We examine this issue by using a loan-level data set from LPS Analytics, covering approximately two-thirds of the mortgages originated in 2005 and 2006, and including both securitized and nonsecuritized loans.

We find evidence that privately securitized loans do indeed perform worse than observably similar, nonsecuritized loans. Moreover, this effect is strongest in prime mortgage markets, which have not been studied in the previous literature. For example, a typical prime loan becomes delinquent at a 20 percent higher rate if it is privately securitized, *ceteris paribus*. This is consistent with the existence of adverse selection; that is, that lenders used information not available to investors to securitize loans that were riskier than they otherwise appeared. By contrast, for subprime mortgages, the impact of private securitization is concentrated in low or no-documentation loans; this latter result is consistent with previous work such as Keys et al. (2009).

INTRODUCTION

One of the notable innovations of the mortgage boom was the dramatic increase in private securitization; by 2005 it made up over 50 percent of all new securitizations (Figure 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 also 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.[1] This has also found support 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 even after the mortgages are 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 view is also supported by earlier work on the securitization of prime mortgages, in particular

[1] http://www.financialstability.gov/docs/regs/FinalReport_web.pdf

Ambrose et al. (2005), who found that securitized loans tended to perform *better* than similar nonsecuritized loans.

More generally, several theories have been proposed for why lenders securitize loans. One is *regulatory arbitrage*; i.e., lenders sell loans in order to remove them from their balance sheets and thereby conserve costly capital (James, 1987). Others have suggested that securitization serves to reduce the scope of assets subject to bankruptcy costs (Gorton and Souleles, 2007). Note that for 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, the 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.[2]

In this paper we find that for prime mortgages, private-securitized loans do indeed perform significantly worse than non-private-securitized loans, after conditioning on publicly available information; in particular, they default at more than 20 percent higher rates. This is consistent with adverse selection, that is, with lenders securitizing loans that were riskier than

[2] Another reason why securitized loans may perform worse is monitoring. This is discussed further below.

they otherwise appeared. Given the large number of prime loans that were originated over this period, this difference in default rates is economically important.

By contrast, in our baseline results we find that the securitized subprime loans actually default at lower rates, ceteris paribus. However, we show that this is completely 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. Taking this into account reverses the sign of the securitization coefficient for subprime loans and for adjustable-rate subprime mortgages, again results in private-securitized loans that are significantly riskier than observably similar non-private-securitized loans.

We also interact private securitization with 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 these loans, and thus we should expect a stronger effect from securitization. For prime mortgages, we do find that the effect of private securitization is modestly stronger for low and no-doc loans, although securitized loans are in fact riskier for all documentation types. For subprime loans, however, the effect of securitization is dramatically larger when there is low or no-documentation. And indeed, for subprime FRM, full-documentation loans exhibit no higher risk when they are securitized; the entire impact of private securitization is for low documentation loans. These results on subprime loans are consistent with the findings of Keys et al. (2009).

Since the LPS data that we use do not contain data 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[3] or the structure of the MBS reflected this additional risk (see Gorton and Souleles, 2007, for an example of this in credit card

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

securitizations, and also Adelino, 2009). Nevertheless, even if this were the case, securitization motivated by adverse selection could still be inefficient, as bad loans would drive out the good – restricting lenders to more expensive on-balance-sheet financing to fund high-quality loans.

RELATED LITERATURE

This paper is not the first one 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 and default rates.[4] They find that those regions in which subprime securitization expanded most rapidly were also those in which default rates subsequently rose. However, their reliance on aggregate data makes interpreting the results difficult. In particular, without detailed information on loan characteristics, this approach does not allow us to easily distinguish the risk-sharing motivation for securitization from adverse selection.

Several other papers have used loan-level information to study the effect of securitization. The most prominent of these is Keys et al. (2009). They 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.

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

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

FICO scores below 620. Furthermore, work by Bubb and Kaufmann (2009) suggests that this "620-discontinuity" also plays a role in the performance of nonsecuritized loans.[5]

From the perspective of our 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. And, indeed, their analysis focuses on subprime loans, and they find a significant effect on only those subprime mortgages with low or no documentation of income. 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 a data set (like LP) that required restricting attention to loans with FICO scores around 620.

Two other papers have used loan-level data sets that include information on both securitized and nonsecuritized loans. The first, Ambrose et al. (2005), considers loans originated by a single lender between 1995 and 1997. As in this paper, they are interested in determining whether asymmetric information motivates securitization and, like us, compare the conditional default rates on securitized and nonsecuritized loans. As discussed above, they find that securitized loans default at lower rates than nonsecuritized loans and conclude that either securitization is in fact motivated by regulatory arbitrage or that reputational incentives are sufficiently strong to keep lenders from taking advantage their information. These results stand in contrast to ours, but it is important to note that our paper considers a much larger set of loans,

[5] See also Krainer and Laderman (2009). Some of these criticisms are addressed by additional analyses that the authors undertake in the paper. In particular, they also examine the introduction, and repeal, of anti-predatory lending laws in Georgia and New Jersey. The results of this latter analysis are consistent with those of their primary approach; during the period that these laws were in force, loans with credit scores slightly above 620 default at higher rates than those with scores slightly below. In addition, see Keys et al. (2010) for a more detailed discussion of these issues.

originated by many different lenders, and that we contrast focus on a time period in which the volume of risky lending (and subsequently, defaults) rose dramatically.

Another paper, Jiang et al. (2010), uses data on loans originated by a single lender between January 2004 and February 2008 (primarily Alt-A 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 to allow individual loans into securitized pools or not. By contrast, we find that securitized loans perform worse, even *ex post*. However, our results are strongest for prime loans, which are under-represented in their sample. And like Jiang et al. (2010), we also find evidence that post-origination selection may have improved the performance of the pool of securitized loans.

DATA DESCRIPTION

Introduction

We use loan-level data from the LPS Applied Analytics Inc, data set.[6] These data have been used to study the determinants of mortgage default by Elul et al. (2010) and also 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 originated in 2005 and 2006, since coverage of the LPS data was not as extensive prior to 2005 (particularly for subprime loans), and since by early 2007 the

[6] This data set is also commonly known as the “McDash” data.

housing market had already showed signs of deterioration. The LPS data cover about 70 percent of all mortgage originations in these years.[7] 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 sample represents about 60 percent of all of the first mortgages in the LPS data. We follow our borrowers through April 2009.

We divide our sample into four distinct subsamples: prime FRM, prime ARM, subprime FRM, and 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. 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.

Variables

The LPS data set is divided into a "static" file, whose values 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, source of the loan (e.g., whether it was broker-originated), property

[7] For example, 7.4 million first mortgage originations were recorded in LPS in 2005, as compared to 10.5 million in the HMDA data, and 6.4 million in 2006, as compared to 8.6 million in HMDA.

location (zip code), type of loan (fixed-rate, ARM, prime, subprime, IO, Option-ARM, etc.), the prepayment penalty period (if any).

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, GNMA, FNMA, FHLMC, 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 also merge in house price index data from the 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 quarterly as well.

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 observables, we will conclude that this is support for the adverse selection hypothesis of securitization.

Our dependent variable is a dummy variable indicating when a mortgage first becomes 60+ days delinquent, i.e., is first reported as having missed two or more payments.[9] This is a relatively early definition of default, as compared to a foreclosure, which can occur many months later. We use this early definition for two reasons. First, state laws governing

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[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 when using a Cox proportional hazard model.

[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.

foreclosure differ widely, and this can have an effect on the length of time it takes to conclude a foreclosure.[10] Also, whether a delinquent loan is securitized or not may also affect the ease of modifying it and hence of avoiding foreclosure, i.e., monitoring (Piskorski, Seru, and Vig, 2010, and Agarwal et el, 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., initial LTV and origination FICO score), all taken from the time of origination. One exception is the investor type, which is determined after 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.

Recall that the data set is constructed to be quarterly. To clarify the timing, we consider whether mortgage i defaults in a given quarter, i.e., in months t+1, t+2, or t+3. The independent variables are all lagged relative to this quarter. The LPS mortgage control variables, most notably the first mortgage balance, come from month t. To be conservative, the variables from the other data sets are lagged one month further. The bureau data are from the last month of the previous quarter, i.e., month t-1. The house price index is the average for the previous quarter, i.e., over months t-3, t-2, and t-1. Finally, the change in the county unemployment rate is taken from months t-13 to t-1.

[10] Many papers have studied the effect of these state laws on foreclosure outcomes; for example, Ghent and Kudlyak (2009) use the LPS data to address laws that restrict deficiency judgments.
[11] But see Foote et al. (2009) for an opposing view.

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 it in more detail. The investor types available in the LPS data set are "portfolio," "GNMA," "FNMA," "FHLMC," and "private-securitized;" for the purposes of this paper we combine FNMA and FHLMC-securitized loans into a single category: "GSE". These investor types are dynamic and can change every month. In Figure 2 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 on which the second payment was 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 the type reported at six months from loan origination. This is early enough to avoid most defaults (but see our discussion of early defaults, below), 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. For our estimations, we also define a binary variable, which captures whether or not the final investor type is "private-securitized."

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

[13] This is also the definition used by Bubb and Kaufman (2009). In an earlier version of this paper we considered a different definition of the investor type and obtained nearly identical estimation results.

ESTIMATION AND RESULTS

Introduction

To motivate our analysis, we begin by plotting nonparametric default hazard functions for both private-securitized and non-private-securitized loans, in Figure 3. 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 non-private-securitized loans. It is also interesting to observe that the impact of securitization is smaller in the subprime market, with non-private-securitized subprime ARMs actually defaulting at lower rates early in their lives. As we demonstrate below, this difference is attributable to loans that default early - before they can be securitized. We now study this more formally in a multivariate framework.

Baseline Results

Tables 3a and 3b report the point estimates and marginal effects for our baseline specification. Beginning with the prime subsamples in Table 3a, we first note that the marginal effects for the variables commonly used in mortgage default studies have the expected signs. For example, for prime FRM, broker-originated loans have a 0.247 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, while loans with higher interest rates, larger loans, and loans with private mortgage insurance (PMI) are all riskier. The effect of initial LTV is negative for three out of our four subsamples. 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). Turning now to the variable of interest, the private securitization coefficients for the prime subsamples are positive and statistically significant. To gauge the economic impact, observe that for prime FRM, the marginal effect of private securitization is 0.229 pp/q, and for prime ARMs it is 0.402 pp/q, significant compared to the sample average default rates of 0.9 pp/q and 2 pp/q, respectively. That is, private-securitized loans default at higher rates, after controlling for observables. As discussed above, this supports the hypothesis that lenders use private information to determine which loans to securitize.

For the subprime samples, the majority of the coefficients for the control variables are similar. However, the private securitization coefficients are negative; that is, private-securitized loans default at lower rates, *ceteris paribus*. As we now discuss, this is attributable to "early defaults."

Early Default and Securitization

To understand why private-securitized subprime loans appear to be less risky in the baseline results above, 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 well have intended to sell very risky loans to securitized pools, but 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: 17 percent of all subprime FRM and 21 percent of all subprime ARMs originated during these years.

To control for this, we rerun our baseline model, but this time we exclude all loans that became delinquent within six months of origination. The point estimates and marginals for private securitization are reported in Table 4. Observe that this has very little impact on the results for prime loans, which is not surprising as only a small fraction of loans fall into this category.[14] The effect on subprime loans is much more dramatic however. Observe that the sign of the securitization coefficient is reversed, and for adjustable-rate subprime mortgages, it results in securitized loans that are significantly riskier. Thus as in Jiang et al. (2010), we find that post-origination 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 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.

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, as low documentation loans are precisely those for which the asymmetry of information is greatest. That is, given the paucity of verified “hard” information

[14] In fact, the effect of private securitization is modestly smaller for both prime subsamples than in our baseline specifications, likely because we have eliminated some defaulting loans from the sample.

for these borrowers, lenders may well have collected additional “soft” information, which was not shared with investors. Thus, we also interact the private securitization indicator with the documentation type of the loan (that is, whether income and assets are documented). The results are reported in Table 5.

For prime mortgages, we find that while private-securitized loans are riskier for all documentation types, the effect is indeed modestly stronger for low and no-doc loans. Furthermore, for subprime loans, the effect of securitization is much more pronounced when there is low or no-documentation. Indeed, for subprime FRM, full-documentation loans are in fact no riskier when securitized; the entire impact of securitization is concentrated in low documentation loans. This is consistent with the findings of Keys et al. (2009).

Adverse Selection vs. Monitoring

As discussed earlier, an alternative explanation that has been proposed for the higher default risk of private-securitized loans is monitoring; that is, servicers have less incentive to modify or otherwise work out loans that they do not own. Piskorski, Seru, and Vig (2010) find that, conditional on being seriously delinquent (90+ days late), loans that are private-securitized are more likely to be foreclosed. Similarly, Agarwal et al. (2011) show that distressed bank-held loans are more likely to be renegotiated than similar securitized mortgages. By contrast, Adelino et al. (2010) find little effect from securitization.

Note that even if securitization affects servicers’ post-origination behavior, this does not rule out the existence of adverse selection. However, in order to ensure that the results that we obtain truly reflect lender behavior at origination, we rerun our model using the earliest possible definition of default – the missed payment (i.e., a first delinquency of 30+ days in the quarter).

This is almost certainly the first sign of trouble that servicers would observe for a mortgage, and so the securitization coefficients in this case would isolate the effect at origination.[15] The cost of using this early definition is that a single missed payment is often due to random factors (such as forgetting to mail a payment), which potentially increases the standard errors of our estimates, and thus for the remainder of the paper, we revert to our original definition of default.

In Table 6 we report these results. The effect of private securitization is positive and significant for the prime mortgage samples, just as reported above, and the coefficients on the other control variables (not reported) were also qualitatively similar to those obtained earlier. This supports our conclusion that our results measure the effect of adverse selection at origination.

Lender Fixed Effects

One of the limitations of the LPS data set is that it does not include information on the identity of the lender. This is information that investors could have observed. Thus, its absence leaves open 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 would have recognized. 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 data (HMDA). [16] This gives us an anonymous identifier for each lender, which allows us to rerun our earlier estimations with lender fixed effects.[17]

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[15] However, servicers, could in principle, seek out borrowers who have always been current but are otherwise at risk of default.

[16] 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 5 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 non-owner-occupied), and lien status (first lien or other). The match rate was approximately 50 percent.

The point estimates and marginal effects are reported in Table 7, where we confirm that the effect of private securitization is indeed qualitatively similar to that reported above.

Other Investor Types: the GSE's and Jumbo Mortgages

In the estimations above, we examined the marginal effect of private securitization, combining all other investor types (FHA, GSE, and portfolio) together. But in fact, the distribution of these investor types differs widely across mortgage types, as reported in Table 1. We now examine their role in greater detail.

First, we rerun our earlier estimations but now break out all four investor types individually. Since the GSE and FHA presence in the subprime ARM market was negligible, we restrict attention to the prime FRM, prime ARM, and subprime FRM subsamples. Our results are reported in Table 8.

In every case, observe that private-securitized mortgages are riskier than loans retained in portfolio (the omitted category); the effect is of the same magnitude as in our earlier estimations (with all non-private-securitized loans combined together). Similarly, FHA loans are also always riskier. In the prime markets, private-securitized mortgages are also riskier than GSE loans, with GSE adjustable-rate mortgages even less risky than similar portfolio loans. For subprime FRM, our point estimates for GSE loans are higher than for private-securitized, but the difference is not statistically significant.

Next, we consider the binary choice between private securitization and retaining loans in portfolio. To do so, we rerun our estimations while restricting our sample to "jumbo" mortgages

[17] The anonymity is due to restrictions imposed by the data provider. For tractability, we further restrict attention to loans originated by the top 25 lenders in each subsample.

alone, that is, loans that are too large to meet the GSE underwriting criteria.[18] In this case, the only admissible investor types are portfolio and private-securitized.[19]

Table 9 reports the fraction of jumbo loans that are private-securitized for each of the remaining subsamples. Since the GSEs had little market share in the subprime market (Table 1), it is not surprising that the vast majority of jumbo subprime mortgages are private-securitized. In addition, in the prime FRM jumbo subsample, the private securitization rate is also high, most likely because securitization is a way for lenders to hedge the interest rate risk of fixed-rate mortgages. It is only in the prime ARM segment that lenders retain a significant portion of loans (36 percent).

The effect of private securitization in the jumbo prime ARM subsample (Table 9) is positive and economically significant – and of the same magnitude as for the overall sample in Table 3. This is consistent with the observation above that lenders retained many of these prime ARMs – thus securitizing only worse loans was feasible. For jumbo prime FRM, while the effect of private securitization is still positive, it is smaller than that for the overall sample. Again, since retaining fixed-rate loans in portfolio is costlier, and since the GSE market is not available to purchase the better-quality loans, it is not surprising that the effect of private securitization will be more modest. Finally, just as for the overall sample, the effect of private securitization for jumbo subprime FRM (once we drop early defaulting loans, as discussed above) is positive but statistically insignificant.[20]

[18] In 2005, the conforming loan limit for single-family homes was $359,650, and in 2006 it was $417,000.
[19] FHA loans are also excluded, as FHA-insured loans also cannot exceed the conforming loan limit. We drop the small subset of loans that are above the conforming loan limit for the year of origination but are nevertheless recorded as GSE (or FHA). As they are heavily concentrated in the last months of the year, these mortgages likely reflect loans that only became conforming under the next year's (higher) limit.
[20] Recall that the entire effect of private securitization was concentrated in low-documentation loans for this subsample.

CONCLUSIONS

Using a 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-doc loans). These results are economically important because of the much larger size of the prime mortgage market.

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

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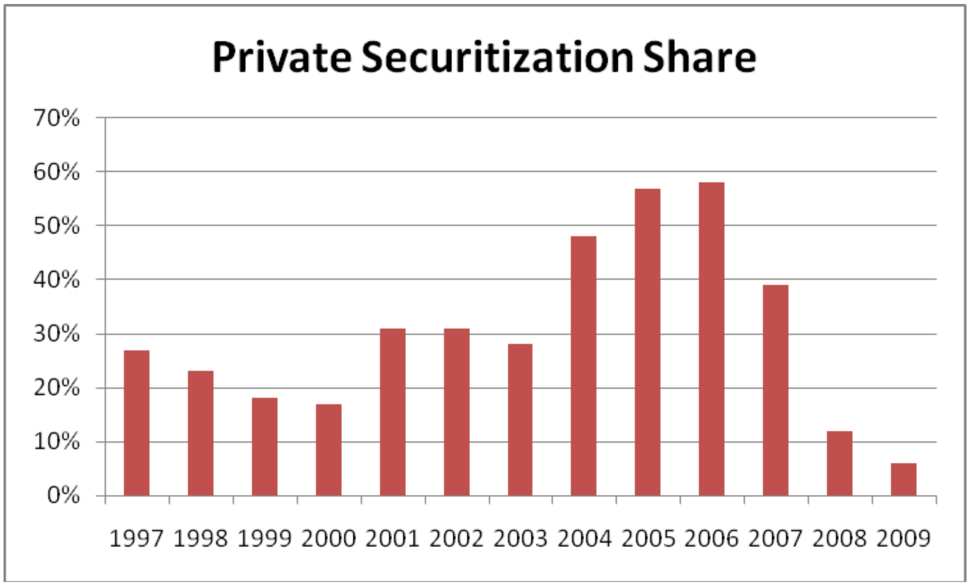
APPENDIX – FIGURES AND TABLES

Figure 1: Private-securitized Mortgages: as a Share of New Securitization[21]



[21] Source: Inside Mortgage Finance

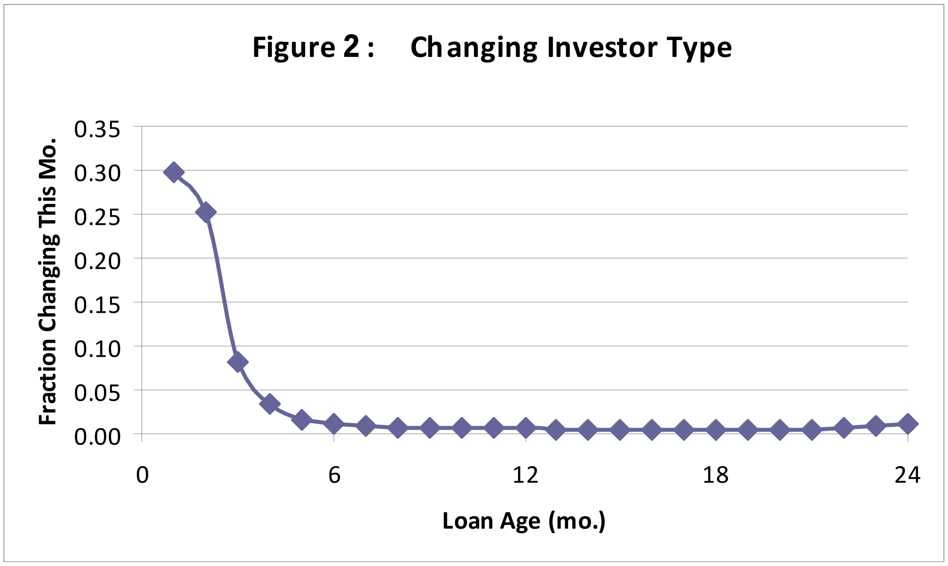


Table 1 – Investor Type at Six Months

	Prime FRM	Prime ARM	Subprime FRM	Subprime ARM	
FHA	0.09	0.01	0.00	0.00	Not Private-securitized
GSE	0.70	0.37	0.16	0.00	
Portfolio	0.05	0.20	0.04	0.09	
Private-securitized	0.16	0.42	0.81	0.91	

Table 2 – Variable Means

	Prime FRM	Prime ARM	Subprime FRM	Subprime ARM
Default in Next Quarter/LHS (%)	0.89%	2.01%	5.45%	7.75%
Loan Age (mo.)	19.2	18.8	16.4	13.6
Private-securitized	0.16	0.42	0.81	0.91
Interest Rate (%)	6.1	6.0	7.7	7.9
FICO at Origination	712	712	609	609
ln(initial loan amount)	12.0	12.5	11.9	12.0
Initial LTV	0.73	0.74	0.77	0.80
Initial LTV=80%	0.13	0.24	0.18	0.26
Interest-Only Loan	0.03	0.61	0.04	0.16
Option-ARM	-	0.11	-	0.27
Jumbo	0.06	0.28	0.06	0.10
Refinancing	0.45	0.38	0.73	0.47
Cash-out Refi.	0.22	0.14	0.59	0.35
Loan has PMI	0.14	0.05	0.01	0.04
Transferred to Servicer	0.09	0.25	0.31	0.26
Prepayment Penalty	0.02	0.09	0.65	0.78
Correspondent Orig.	0.30	0.14	0.19	0.14
Broker Orig.	0.16	0.15	0.18	0.34
Low/No-Documentation	0.16	0.20	0.05	0.15
Condo	0.11	0.20	0.06	0.11
Current LTV	0.67	0.69	0.73	0.75
Unemp Change - Past Yr (%)	0.39	0.38	0.29	-0.06
Delinquent within First 6 Months	0.04	0.07	0.17	0.21
Term (yrs.)				
15	10.1	0.0	4.6	0.0
30	89.3	99.6	85.5	89.1
40	0.6	0.4	9.9	10.9
ARM Fixed Period (mo.)				
24	-	14.2	-	78.6
36	-	9.1	-	19.2
60	-	48.9	-	2.1
84	-	14.1	-	0.0
120	-	13.8	-	0.0

Figure 3: Nonparametric Default Hazard Functions

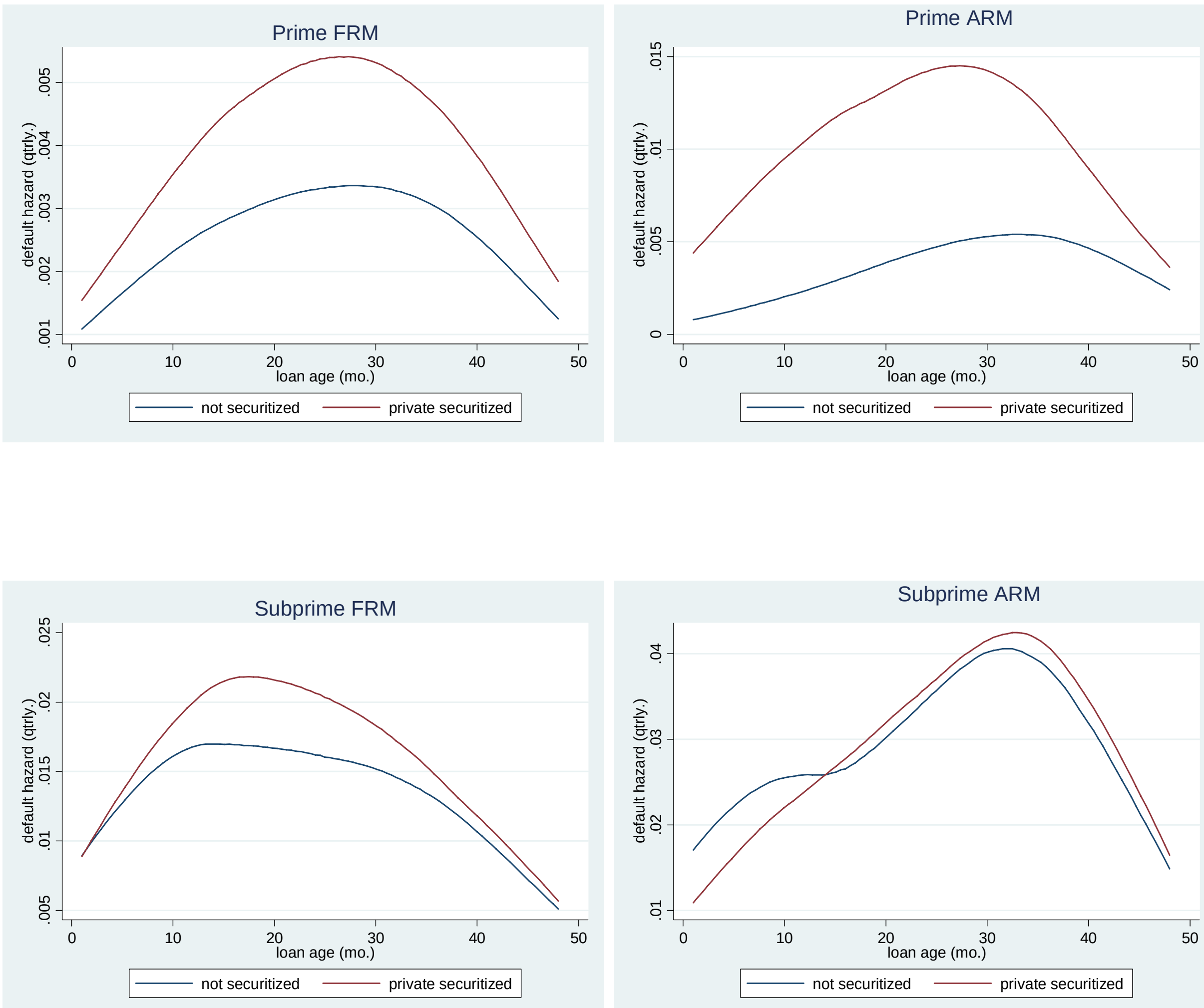


Table 3a: Baseline Estimation – Prime Mortgages[22]

	Prime FRM				Prime ARM			
	Coeff.	**SE**	**Mgl (pct)**	**SE (pct.)**	**Coeff.**	**SE**	**Mgl (pct)**	**SE (pct.)**
Private Securitized	0.241***	0.008	0.229***	0.008	0.235***	0.006	0.402***	0.011
Interest Rate	0.487***	0.005	0.429***	0.069	0.350***	0.003	0.608***	0.113
Initial FICO	0.016***	0.001	-0.011***	0.002	0.031***	0.001	-0.014***	0.003
FICO^2	0.000***	0.000			0.000***	0.000		
ln(initial loan amount)	0.035***	0.006	0.031***	0.007	0.217***	0.007	0.377***	0.071
Initial LTV	0.172***	0.033	0.151***	0.038	-0.107***	0.041	-0.186**	0.079
Initial LTV = 80%	0.108***	0.007	0.098***	0.007	0.247***	0.005	0.446***	0.010
Interest-Only Loan	0.777***	0.011	0.966***	0.018	0.222***	0.006	0.379***	0.011
Option-ARM					-0.145***	0.010	-0.240***	0.016
Jumbo	-0.139***	0.013	-0.116***	0.010	-0.227***	0.009	-0.377***	0.014
Refinancing	-0.053***	0.007	-0.046***	0.006	-0.187***	0.006	-0.318***	0.011
Cash-out Refi	0.049***	0.007	0.044***	0.007	0.037***	0.009	0.065***	0.016
Loan has PMI	0.056***	0.007	0.050***	0.006	0.202***	0.012	0.377***	0.023
Transferred to Servicer	0.216***	0.009	0.206***	0.010	0.410***	0.009	0.745***	0.017
Prepayment Penalty	0.194***	0.014	0.186***	0.015	0.235***	0.007	0.437***	0.014
Correspondent Orig.	0.111***	0.006	0.100***	0.005	0.000	0.009	0.000	0.015
Broker Orig.	0.258***	0.007	0.247***	0.007	0.192***	0.008	0.354***	0.015
Low/no-doc	0.007	0.006	0.006	0.006	0.014**	0.007	0.025**	0.012
Condo	-0.098***	0.008	-0.083***	0.007	-0.175***	0.007	-0.291***	0.011
Current LTV	2.265***	0.026	1.996***	0.320	2.571***	0.029	4.458***	0.825
Δunemployment (%)	0.092***	0.004	0.081***	0.014	0.139***	0.005	0.242***	0.046
Term: 30 years	0.184***	0.013	0.150***	0.010	0.034	0.202	0.057	0.340
Term: 40 years	0.406***	0.025	0.367***	0.026	0.172	0.204	0.312	0.345
ARM Fixed-Rate Period (mo.)								
36					-0.062***	0.010	-0.142***	0.024
60					-0.423***	0.010	-0.842***	0.023
84					-0.666***	0.013	-1.204***	0.024
120					-0.986***	0.013	-1.575***	0.023
N	20.61m				11.02m			
Pseudo-R^2	0.14				0.20			

[22] Dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Quintic in loan age and dummies for state, origination quarter, and calendar time are not reported. Baseline categories: 15-year term, 2/28 ARM, single-family property (not condo), full-documentation. Refinancing is relative to purchase loans (cashout refi is the extra risk on top of refinancing). Private-securitized status at six months from origination. Source: LPS Analytics.

Table 3b: Baseline Estimation - Subprime Mortgages[23]

	Subprime FRM				Subprime ARM			
	Coeff.	SE	Mgl (pct)	SE	Coeff.	SE	Marginal	SE
Private Securitized	-0.131 ***	0.012	-0.684 ***	0.064	-0.321 ***	0.009	-2.451 ***	0.072
Interest Rate	0.270 ***	0.004	1.359 ***	0.317	0.222 ***	0.002	1.530 ***	0.137
Initial FICO	0.006 ***	0.001	-0.029 ***	0.007	-0.004 ***	0.001	-0.028 ***	0.003
$FICO^2$	0.000 ***	0.000			0.000	0.000		
ln(initial loan amount)	0.334 ***	0.008	1.682 ***	0.395	0.291 ***	0.006	2.003 ***	0.182
Initial LTV	-1.077 ***	0.051	-5.430 ***	1.292	-1.635 ***	0.042	-11.259 ***	1.038
Initial LTV = 80%	0.230 ***	0.008	1.229 ***	0.046	0.215 ***	0.005	1.540 ***	0.036
Interest-Only Loan	0.553 ***	0.015	3.436 ***	0.115	0.059 ***	0.006	0.411 ***	0.045
Option-ARM					-0.035 ***	0.007	-0.239	0.047
Jumbo	-0.038 **	0.015	-0.191 **	0.075	-0.006	0.008	-0.042	0.058
Refinancing	-0.454 ***	0.012	-2.495 ***	0.070	-0.304 ***	0.008	-2.071 ***	0.052
Cash-out Refi	0.060 ***	0.011	0.302 ***	0.055	0.027 ***	0.008	0.188 ***	0.057
Loan has PMI	-0.214 ***	0.040	-0.992 ***	0.169	-0.159 ***	0.013	-1.035 ***	0.083
Transferred to Servicer	0.320 ***	0.009	1.708 ***	0.052	0.341 ***	0.007	2.536 ***	0.056
Prepayment Penalty	-0.048 ***	0.010	-0.246 ***	0.051	-0.067 ***	0.008	-0.467 ***	0.054
Correspondent Orig.	0.030 ***	0.010	0.155 ***	0.052	0.207 ***	0.008	1.511 ***	0.060
Broker Orig.	0.079 ***	0.010	0.407 ***	0.052	0.326 ***	0.007	2.330 ***	0.054
Low/no-doc	0.094 ***	0.015	0.491 ***	0.082	0.193 ***	0.007	1.399 ***	0.051
Condo	-0.081 ***	0.013	-0.397 ***	0.063	-0.121 ***	0.007	-0.806 ***	0.043
Current LTV	2.124 ***	0.045	10.703 ***	2.505	2.584 ***	0.036	17.795 ***	1.595
Δunemployment (%)	0.052 ***	0.006	0.261 ***	0.069	0.102 ***	0.004	0.700 ***	0.069
Term: 30 years	0.235 ***	0.020	1.053 ***	0.082	-0.264	0.346	-2.003	2.901
Term: 40 years	0.553 ***	0.023	2.842 ***	0.105	-0.224	0.346	-1.727	2.901
ARM Fixed Period (mo.)								
36					-0.043 ***	0.006	-0.297 ***	0.041
60					-0.254 ***	0.014	-1.604 ***	0.082
84					-0.859 *	0.519	-4.300 **	1.759
120					-0.485 ***	0.184	-2.800 ***	0.862
N	1.96m				3.45m			
Pseudo-R^2	0.08				0.07			

[23] Dependent variable is 60+ days delinquent in next three months, with subsequent observations dropped after the first such default. Quintic in loan age and dummies for state, origination quarter, and calendar time are not reported. Baseline categories: 15-year term, 2/28 ARM, single-family property (not condo), full-documentation. Refinancing is relative to purchase loans (cashout refi is the extra risk on top of refinancing). Private-securitized status at six months from origination. Source: LPS Analytics.

Table 4: No Early Default[24]

Effect of Private Securitization

	Coeff.	SE	Marginal	SE
Prime FRM	0.261	0.009	0.197%	0.007%
Prime ARM	0.249	0.007	0.345%	0.033%
Subprime FRM	0.006	0.015	0.023%	0.054%
Subprime ARM	0.072	0.011	0.343%	0.051%

Table 5: Interaction – Private Securitization and Documentation Type[25]

Effect of Private Securitization

		Marginal	SE
Prime FRM	**Full**	0.223%	0.008%
	Low	0.260%	0.018%
Prime ARM	**Full**	0.380%	0.011%
	Low	0.499%	0.021%
Subprime FRM	**Full**	-0.028%	0.055%
	Low	0.689%	0.154%
Subprime ARM	**Full**	0.243%	0.059%
	Low	0.686%	0.105%

[24] All samples restricted to loans that did not miss any payments in the first 6 months from the loan origination. Other covariates are as in Table 3 and are not reported.
[25] Subprime samples (only) are restricted to loans that did not miss any payments in first 6 months from the loan origination. Other covariates are as in Table 3 and are not reported.

Table 6: First Missed Payment[26]

Effect of Private Securitization

	LHS: First 30-Day Delinquency			
	Coeff.	SE	Marginal	SE
Prime FRM	0.168	0.005	0.334%	0.011%
Prime ARM	0.136	0.005	0.377%	0.014%
Subprime FRM	0.019	0.012	0.113%	0.074%
Subprime ARM	0.052	0.010	0.389%	0.070%

Table 7: Lender Fixed Effects[27]

Effect of Private Securitization

	RHS: Lender F.E.			
	Coeff.	SE	Marginal	SE
Prime FRM	0.291	0.013	0.248%	0.013%
Prime ARM	0.104	0.011	0.147%	0.016%
Subprime FRM	0.064	0.029	0.222%	0.097%
Subprime ARM	0.031	0.027	0.146%	0.125%

[26] Dependent variable is 30+-day delinquency in the next three months. Other covariates are as in Table 3 and are not reported. Subprime samples (only) are restricted to loans that did not miss any payments in the first 6 months from the loan origination.

[27] Restricted to loans originated by top-25 lenders in each subsample; fixed effects for these lenders were included but are not reported. Other covariates are as in Table 3 and are not reported. Subprime samples (only) are restricted to loans that did not miss any payments in the first 6 months from the loan origination.

Table 8: All Investor Types[28]

	Prime FRM				Prime ARM				Subprime FRM			
	Coeff.	**SE**	**Marginal**	**SE**	**Coeff.**	**SE**	**Marginal**	**SE**	**Coeff.**	**SE**	**Marginal**	**SE**
FHA	0.012	0.014	0.011%	0.013%	0.378	0.030	0.633%	0.057%				
GSE	-0.113	0.012	-0.098%	0.011%	0.178	0.009	0.272%	0.014%	0.081	0.030	0.293%	0.106%
Private Securit.	0.152	0.013	0.149%	0.013%	0.322	0.008	0.527%	0.012%	0.057	0.024	0.203%	0.083%

Table 9: Jumbo Mortgages[29]

Effect of Private Securitization

	Coeff.	SE	Marginal	SE	N	Priv. Secur. Frac.
Prime FRM	0.122	0.052	0.089%	0.036%	1,225,027	0.92
Prime ARM	0.348	0.013	0.433%	0.015%	3,316,302	0.64
Subprime FRM	0.109	0.101	0.436%	0.391%	104,487	0.97
Subprime ARM	0.013	0.030	0.076%	0.180%	273,432	0.91

28 The results are relative to loans retained in the lender's portfolio, the omitted investor type. Subprime ARMs dropped as there was negligible GSE and FHA participation in this market. The subprime FRM subsample did not include any FHA loans. The subprime FRM sample also further restricted to loans that did not miss any payments in the first 6 months from the loan origination. Other covariates are as in Table 3 and are not reported.

29 The sample was restricted to mortgages larger than the conforming loan limit in the year of origination ("jumbo loans"); any remaining loans coded as GSE or FHA were dropped. The effect of private securitization is relative to portfolio loans. Subprime samples (only) are restricted to loans that did not miss any payments in the first 6 months from the loan origination. Other covariates are as in Table 3 and are not reported.