Information Loss in Mortgage Securitization: Effect on Loan Modification[*]

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Abstract

Tracking a sample of modified loans underlying private-label mortgage-backed securities, I compare the modification effectiveness of servicers who originated mortgages versus those who simply service loans. The probability of re-default among loans modified by the former is over 25% lower than the latter. Further tests show that the differences in modification success likely come from the soft information acquired during the origination process. These findings suggest that the loss of soft information in mortgage securitization can impose a substantial cost on mortgage servicing, which raises important policy implications for government regulations in this market.

Key words: *mortgage, modification, originator, servicer, soft information*

JEL classification: G2, G01, G18, D82

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I. Introduction

Following the financial crisis, one of the most prominent concerns of mortgage securitization is the potential conflicts of interest resulting from the separation of a loan's originator and its ultimate owners. These concerns arise from the lenders' lack of incentives to carefully screen borrowers in the initial loan underwriting process. Indeed, several studies have argued that the lax lending standards adopted by virtually all creditors during the pre-2007 credit boom should take the primary blame for the ensuing collapse of the subprime mortgage market (see, for example, Dell'Ariccia, Igan, & Laeven, 2008; Keys, Mukherjee, Seru, & Vig, 2010; Kruger, 2014; Mian & Sufi, 2009; Purnanandam, 2011).[1] Demiroglu & James (2012) show that retaining more "skin in the game", through becoming the sponsors or servicers of mortgage-backed securities (MBS), can help alleviate the incentive problem on the part of loan originators. In addition, since originators know the quality of the loans they originate, they can use this private information to cherry-pick better loans to keep in their portfolio while offloading subpar loans to MBS investors (Agarwal, Chang, & Yavas, 2012; Ambrose, Lacour-Little, & Sanders, 2005; Elul, 2016).[2]

The focus of research thus far is on the asymmetric information problem at the time of loan origination and securitization. This paper extends the existing literature by examining whether the transfer of mortgages to the security market also creates challenges for servicers in managing loan performance. In particular, I study the effectiveness of servicers in performing loan modification when a borrower defaults. Generally, the lender has several options when dealing with defaults

[1] Dell'Ariccia et al. (2008) and Mian & Sufi (2009) provide empirical evidence that credit became significantly more available during the period leading to the crisis. Such a sharp increase in credit growth was followed by an unprecedented increase in mortgage defaults, as found in Mian & Sufi (2009) and Keys et al. (2010).

[2] Consistent with the adverse selection hypothesis, Elul (2016) finds that securitized loans have a higher default rate than portfolio loans. On the other hand, using data from the 1990s, Ambrose et al. (2005) show that the loans retained in portfolios have a higher default risk, likely due to capital arbitrage or concern for reputation. Interestingly, Agarwal et al. (2012) find that lenders retain loans with higher default risk but lower prepayment risk relative to the loans they sell to the secondary market.

(usually defined as missing at least three payments): forebear on the delinquency, modify the loan terms, allow a short sale (whereby borrower can sell the property at a price lower than the remaining loan balance), or foreclose on the property.[3] In the midst of the latest financial crisis, the unprecedented volume of foreclosures prompted pressing calls for greater use of the loan modification option, as it is often believed to be less costly for both borrowers and lenders.[4] However, loan modification is not without cost. The decision to modify a loan depends mostly on the ability of the lender to determine if the borrower can continue to make their payment after receiving assistance. This task requires the lender to carefully collect and evaluate costly information about the financial conditions of the borrower.[5] While it is in the interest and the responsibility of the loan originators to carry out these tasks if the loan is held on their balance sheets, in the case of securitized mortgages, the servicers are in charge of making such decisions on behalf of MBS investors.

Several possible explanations exist for why originators can be more successful than servicers in performing loan modification. Consider the informational advantages of originators as an example. While some information on the borrower's characteristics, such as FICO score, can be credibly documented and transferred to servicers after securitization, other important soft information, such as the loan officer's assessment of the borrower's personality, that is unverifiable and importable may be lost. Therefore, originators may have informational advantages over any other subsequent institutions involved in handling the mortgages. In other words, information obtained during loan origination can be valuable for servicers in making their decisions to modify

[3] See Ambrose & Capone (1996) for an analysis of the different foreclosure alternatives.

[4] Maturana (2014) estimates that an additional modification reduces loan losses by as much as 40% relative to the loan average loss of 40.5%.

[5] Eggert (2007) estimates the cost of modification to be between $500 and $600 per loan. In addition to expensive monetary expenses, loan modification also brings about moral hazard problem on the part of borrowers (Mayer, Morrison, Piskorski, & Gupta, 2014; Riddiough & Wyatt, 1994; Wang et al., 2002).

troubled loans, but is not available to them. In this paper, I present several empirical tests to explore various hypotheses about what drives the performance of servicers in loan modification.

The empirical strategy in this paper makes use of the fact that in several MBS deals the loan originators retain the servicing rights to the securitized loans (I refer to these as originator-servicers, or OS). Hence, a comparison of the re-default probability of mortgages modified by OS to those modified by non-OS can shed light on this study's research questions.[6] Nonetheless, the challenge in estimating such effect is that retaining servicing rights is an endogenous choice for originators. Similar to the adverse selection problem arising when originators decide to keep safer loans on their books and securitize riskier ones, one can question whether originators cherry-pick mortgages of better quality to retain in their servicing portfolios. In support of this reasoning, Demiroglu & James (2012) compare the ex-post foreclosure rates of securitized mortgages and find a lower rate among those whose originators are affiliated with their servicers. Comparing the observable characteristics of OS and non-OS loans, I confirm that the former appear to have lower observable risk profiles, such as higher FICO scores and lower loan-to-value (LTV) ratios. Furthermore, they have lower default rates on average, even after controlling for observable loan attributes, which implies that originators also make their selection based on unobservable quality.

To control for this endogeneity problem, I select a sample of comparable loans that include only high-quality non-OS loans and low-quality OS loans, using loan age at securitization as a proxy for unobservable quality. Specifically, the sample includes only non-OS loans that were securitized more than two years after their origination, and OS loans securitized within six months from origination date. The rationale behind this identification strategy is that loans that have

[6] Some loans may receive modification even before they are officially in default, because the servicers/lenders may have foreseen the borrowers' difficulties; thus, the term "re-default" might not appear appropriate in these cases. Nevertheless, for simplicity, throughout this paper re-default is defined as a default occurrence after a loan has been modified.

performed for at least two years before being securitized are likely high quality loans, while those sold quickly are often risky, conduit-type loans originated solely for the purpose of securitization. Comparing their post-securitization default rate, I confirm that the latter group indeed has higher default risk than the former, justifying my assumption that loan age at securitization can act as a signal of loan quality.

After controlling for their quality difference, OS loans are found to have a considerably lower probability of re-default. More specifically, the probability of re-default within 6 months after receiving modification for OS loans is 29% lower than non-OS loans. The differences are 25.6% and 26.5% when examining re-defaults within 12 months and 24 months, respectively. In addition, further tests provide insights about possible explanations behind this observation. I find that OS have certain advantages that allow them to better evaluate and select loans for modification. Such advantages likely come from soft information acquired during the origination process, as evidenced in the finding that OS are most effective in modifying loans whose success rate is more difficult to assess, and that their superior performance dissipates as the modification is done further from the origination date. The large difference in the re-default rates of OS and non-OS loans underscores the important advantages an originator has over other institutions in assessing their borrowers. It is particularly essential for practitioners as well as policy makers to recognize that the loss of soft information in mortgage securitization can impose a substantial cost on the effectiveness of servicers in performing such important tasks as loan modification.

2. Literature review

Although theoretical work on mortgage workouts has existed since Ambrose & Capone (1996), the majority of the empirical research was motivated only recently as a result of the foreclosure crisis in 2008. Securitization plays a central role in the massive development of the

mortgage market since 2000. Given the high foreclosure rate relative to modification rate in the recent crisis, many papers have explored the theory that securitization presents a major barrier to loan modification.[7] Agarwal, Amromin, Ben-David, Chomsisengphet, & Evanoff (2011) document that bank-held loans are 26%-70% more likely to be renegotiated than comparable securitized mortgages, after controlling for servicer fixed effects. However, this type of study is often plagued with the selection issue concerning the possibility that originators can choose to sell loans of lower quality to investors. To overcome this problem, Piskorski, Seru, & Vig (2010) make use of the early pay default (EPD) clauses in many Pooling and Servicing Agreements to design a quasi-experiment, and find that the foreclosure rate of delinquent loans held in bank portfolios is 13% to 32% lower than similar securitized loans.[8] However, Adelino, Gerardi, & Willen (2013, 2014) challenge the above claim based on the fact that investors in reality do not strictly enforce EDP clauses. Adelino et al. (2014) seek to improve their method through a two-stage approach to achieve identification and find no differences in the renegotiation rates for securitized loans and loans held on banks' balance sheets, thereby refuting the prevalent conclusion in other research that securitization creates frictions to loan modification. A similar conclusion is also found in Foote et al. (2009). Another recent attempt to settle this debate by Kruger (2014) uses a quasi-experiment

[7] As pointed out in Eggart (2007), there are three possible hurdles for servicers. Firstly, loan modification is labor intensive and time consuming, essentially equivalent to re-underwriting the mortgages. Secondly, the compensation structure of services does not cover these extra modification costs. In particular, the main source of income for servicers is their monthly servicing fee, which is a fixed percentage of the unpaid principal balance of the loans in the pool. When dealing with defaults, although successfully keeping a loan alive might help maintain the servicer's future income, the servicer can recover foreclosure cost but not modification cost. In the recent foreclosure crisis, record default rates caused servicers to favor cost-cutting through automated foreclosure processes rather than risking incurring modification costs with a low likelihood of success. Finally, the conflict of interest between servicers and borrowers as well as investors further worsens the modification disincentive problem. In fact, anecdotal evidence shows that many servicers have engaged in abusive practices to increase their income at the expense of borrowers.

[8] EPD clauses demand issuers to repurchase mortgages that become delinquent within 90 days after securitization. Essentially, whether a borrower first misses a payment in the third or fourth month after issuance is close to random but the former group will ultimately be repurchased and end up on a bank's portfolio. Thus, by restricting their analysis to default loans surrounding the 3-month cutoff, Piskorski et al. (2010) argue that they have a plausible instrument for securitization.

to estimate that securitization increases the probability of foreclosure by 4.7 percentage point and decrease the probability of modification by 3.6 percentage point.

In an earlier paper, Adelino et al. (2013) develop a theoretical model to explain renegotiation activities. Their theory is built upon the information asymmetry problem mentioned in Wang et al. (2002) that borrowers have private information about their financial conditions and willingness to repay the mortgage. In particular, modification rates will be lower when it is more difficult for lenders and servicers to evaluate borrowers' ability and willingness to repay the mortgage. Adelino et al. (2013) find a negative correlation between modification rates and self-cure rates of delinquent loans, which serve as a proxy for the information problem, for the period from 2005 to 2010. Such a finding is in stark contrast with the securitization explanation often cited by others.

Advocates of the securitization hypothesis usually compare the low modification rate in the recent crisis with the prior period when securitization was uncommon. However, there is no concrete evidence about the popularity of loan workouts until Ghent (2011). Using a sample of mortgages originated in New York during the Great Depression when mortgage securitization was almost non-existent (1920-1939), she shows that less than 2% of outstanding loans received any concessionary modification. In other words, loan modification was as rare in the old days as it is during the latest era. Therefore, the debate on the effect of securitization on post-default outcomes remains unresolved in the current literature, notwithstanding several attempts to reconcile the evidence. Although it is tempting to blame securitization for the lack of modification effort by servicers, many studies have proven that there are other elements to the story.

Despite its importance, research on the factors affecting the success rate of loan modification is sparse. Overall, studies in this area have suggested that the probability of re-default

depends on the type and timing of modification, the characteristics of the borrowers, and whether the loan is securitized (Acoca & Wachter, 2012; Adelino et al., 2013; Agarwal, Amromin, et al., 2011; Goodman, Ashworth, Landy, & Yang, 2011a, 2011b; Haughwout, Okah, & Tracy, 2010; Quercia & Ding, 2009; Voicu, Jacob, Rengert, & Fang, 2012). Das & Meadows (2013) develop a model conjecturing that, among the various ways to lower monthly payment for borrowers, reducing the principal amount (which effectively reduces LTV ratio) is the optimal type of loan modification. By writing down the LTV ratio, lenders lower both the payment burden and the incentive for strategic default for borrowers.[9] Empirical tests by Quercia & Ding (2009) as well as Haughwout et al. (2010) confirm the above theoretical predictions, but they also acknowledge that their small samples have limited statistical power because principal forbearance is very rare. On the other hand, Agarwal, Amromin, et al. (2011) find that greater reductions in interest rates are associated with lower re-default rates. There are conflicting findings regarding the effect of extending loan duration on re-default probability, with a positive correlation found in Voicu et al. (2012) and a negative link found in Agarwal, Amromin, et al. (2011). Finally, Quercia & Ding (2009) assert that earlier intervention helps reduce the risk of subsequent defaults.

Not surprisingly, the success rate of loan modification also depends to a great extent on the characteristics of loans and borrowers. For example, the post-modification performance of high FICO score loans, full document loans, smaller balance loans, loans with positive equity, refinance loans, prime loans, first lien loans, and fixed rate loans is superior to their counterparts (Adelino et al., 2013; Agarwal, Amromin, et al., 2011; Goodman et al., 2011a; Haughwout et al., 2010; Quercia & Ding, 2009). Agarwal et al. (2011) also show that modifications of bank-held loans are

[9] There are two main reasons driving default decisions: negative equity (low willingness to pay) and negative income shock (low ability to pay). If the value of the house falls below the outstanding mortgage balance (negative equity), it is optimal for borrowers to default (strategic default). Reducing LTV ratio will help alleviate the negative equity problem, thereby lowering the incentive to default for borrowers.

more efficient as they have 9% lower re-default rates than mortgages underlying MBS. Interestingly, Zhang (2013) shows that the differences self-cure and re-default rates between the two types of loans converge in the long run.

In an independent, but related paper, Conklin, Diop, & D'Lima (2016) also study the effect of servicer-originator affiliation on loan modification. Despite the strong similarities, our papers differ and complement each other in several aspects. In particular, I focus exclusively and extensively on the performance of loan modification, while Conklin et al. (2016) provide a more comprehensive study on the likelihood of loan modification. Although they observe a lower re-default rate among loans modified by servicers who are related to originators, Conklin et al. (2016) do not address the endogeneity problem concerning the choice of originators to retain safer loans in their servicing portfolios. In addition, Conklin et al. (2016) do not examine the driving forces behind the observed superior performance of affiliated servicers. Lastly, our empirical models, definitions of re-default as well as definitions of originator-servicer affiliation differ. Hence, our papers are natural complements that contribute to the understanding of the performance of MBS servicers in loan modification.

3. Data

The data used in this study come from Blackbox Logic (BBx), a large database of non-agency mortgages underlying more than 90% of the residential mortgage-backed securities market in the U.S. BBx aggregates data from mortgage servicing companies and standardizes them to ensure consistency across different data providers (see www.bbxlogic.com for more information). It provides detailed information on borrower, property and loan characteristics at origination, as well as the monthly performance of each loan from 2000 to 2013. In this study, I focus on subprime loans whose information about originators and servicers are available in the database. After

filtering, the sample has 532,116 loans, and their summary statistics are reported in Panel A of **Table 1**.[10] The average mortgage in my sample has similar characteristics as one would expect of a subprime loan in the market, with a FICO score of about 585, principal of $197,334, LTV ratio of 80%, loan term of 359 months, and annual interest rate of 8.63%. The majority of them are ARM loans (76%), and 38% have low or no documentation.

As described earlier, the variable OS is an indicator for a loan originated and serviced by the same financial institution, which can be identified by matching the names of its originator and servicer in the BBx database. Approximately 10% of the sample are OS loans. I identify OS using an exact originator and servicer name match to ensure that they are the same entity. A broader approach to defining the OS variable would consider whether the two institutions are affiliated with each other, such as in a subsidiary-parent company relationship. However, identifying affiliation among servicers and originators is particularly tricky during and after the 2008 financial crisis when the market went through a large wave of bankruptcies, mergers and acquisitions. In light of such complications, I employ the stricter definition requiring the two entities to have the same name in order to qualify as an OS. As a result, the estimates of the OS impact are biased away from finding an effect because the non-OS group may include mortgages whose servicers are related to the loan originators. Thus, my estimated coefficient for the OS effect is a conservative approximation of the true effect.

Although the sample covers mortgages originated from as far back as 1978, the majority of them concentrate within the short window from 2005 to early 2007, with a peak of 101,980 loans originated in the second quarter of 2006. The top ten originators account for more than 56%

[10] The following loans are excluded from the final sample: original balance less than $40,000, LTV ratio less than 25% or more than 100%, and loan term less than 5 years.

of the sample, while the remaining market were shared by 2,084 smaller institutes (Table A1 in the appendix lists the top ten originators and servicers in the sample). New Century is the largest originator in terms of the number of loans issued, followed by Option One and Fremont. In comparison, the sample of servicers is much smaller with only 80 entities, but the market is also dominated by only a few big players. The largest servicer, Ocwen, is responsible for 28% of the sample (see Table A1).

The focus of this paper, however, is the performance of mortgages that received modification during the study period. The sample of modified loans has 176,961 observations and their summary statistics are shown in Panel B of **Table 1.** With more than half of the sample originated and modified during the mortgage crisis (2005-2007), it is not surprising that 60% of the modified loans re-defaulted within 24 months, where default is defined as at least 90 days delinquency. The rates of re-default within 12 months and 6 months are lower at 44% and 23%, respectively, but are still considerably high. Only 3% of this sample are OS loans, and 3% are bought for investment purposes. At the time of modification, a loan in my sample had slightly less than 320 months remaining in its term. Given that the average loan term in the full sample is 359 months, this implies that the average borrower had made payments for close to 3.5 years when he received loan modification.

I also estimate the amount of negative equity for each mortgage at the time of modification using the Federal Housing Finance Agency (FHFA) housing price index. On average, the outstanding balance was equivalent to about 98.84% of the collateral value when the borrower received assistance.[11] Nonetheless, there is a wide range of negative equity among borrowers in

[11] The value of the property at modification is estimated by multiplying its value at origination by the change in the FHFA housing index for the corresponding metropolitan area. Negative equity is then calculated as the LTV ratio at modification minus one.

the sample, as indicated by the standard deviation of 29.56%. Four common types of modification are listed in the last four rows of Panel B. Capitalizing arrears is most widely used (83% of the sample), followed by interest rate reduction (79%). In capitalization modification, the delinquent amount is added to the outstanding balance and the borrower is brought to current. This is the most popular method in general, and is often used in combination with other modification types. In comparison, lenders are much more reluctant to reduce principal (41% of the sample), as it requires them to immediately recognize a loss. Only 1% of the loans received term adjustment.

4. Empirical methodology

To test the hypothesis that OS are more effective than non-OS in performing loan modification, I select loans that were modified at least once during the study period and track their performance up to two years after modification. The baseline regression model has the following form:

$$Pr\{Redefault_i\} = \Phi(\alpha + \gamma OS_i + \beta Z_i + \mu S_i + \delta_{sv} + \delta_s + \delta_t + \varepsilon_i). \quad (1)$$

The dependent variable, *Redefault*, takes the value of 1 if loan *i* defaulted within 6 months after modification. For robustness, I also use 12 months and 24 months as alternative cutoffs. This post-modification default rate is used as a measure of the servicers' success in modifying troubled mortgages. The main explanatory variable of interest is *OS*, which is the indicator for a loan modified by an OS. Its coefficient, γ, is expected to be negative if the proposed hypothesis holds. The set of control variables Z_i include type of interest rates (ARM or fixed rate), an indicator for low-doc loans, an indicator for investment property, remaining term, and an estimate of the borrower's equity position at the time of modification. In addition, vector Z_i also includes four dummy variables for four types of loan modification: reducing principal, adjusting term, adjusting

interest rate, and capitalizing arrears.[12] The set of control variables S_i include two metropolitan-level factors that are important in affecting borrowers' default risk. To account for movement in the housing market, I include the change in the FHFA house price index (HPI) of the metropolitan area (MSA) where the property is located. The change is calculated over the period from the quarter of modification until the time of default. In a similar manner, the change in the MSA-level unemployment rate is also included in vector S_i as a measure of the movement in broad economic conditions. Finally, the model also controls for servicer fixed effects δ_{sv}, state fixed effects δ_s, and modification month fixed effects δ_t.

4.1. Quality difference between OS and non-OS loans

An important concern in estimating the above model is the selection bias problem associated with the originators' ability to cherry-pick loans to retain in their servicing portfolios. Put it another way, if originators can take advantage of their private information to select low risk loans when bidding for servicing rights, we will observe a lower re-default rate among OS loans that simply results from their lower ex-ante risk. Thus, prior to examining their post-modification performance, I investigate if there exist any systematic differences in the characteristics of OS versus non-OS loans using the following linear probability model:

$$\Pr\{OS_i\} = \Phi(\alpha + \beta X_i + \delta_o + \delta_s + \varepsilon_i), \quad (2)$$

where OS_i=1 if loan i is an OS loan, and X is a vector of loan characteristics at the time of origination, including FICO score, principal amount, loan term, LTV ratio, interest rate, interest type (fixed rate or ARM), and documentation type (full or low/no documentation). The model includes a set of originator fixed effects δ_o to control for their heterogeneity, as well as a set of

[12] Note that a loan can receive more than one type of modification.

state fixed effects δ_s. It is important to note that only mortgage originators who also own a servicing business can choose to service the loans they originate. Originators without servicing businesses, most likely small organizations, do not have such an option and have to sell all servicing rights to an outside institution. By controlling for originator fixed effects, the above regression essentially includes only loans originated by lenders who have servicing businesses, ensuring that the results truly reflect their selection decisions. The first column in **Table 2** reports the estimation results of equation (2). All coefficients are statistically significant at the 1% level. In line with the popular conjecture that originators strategically retain their exposure to low risk loans, **Table 2** provide evidence that OS loans tend to have a higher FICO score, smaller loan amount, lower LTV ratio, shorter term and lower interest rate than their counterparts. They are also more likely to be low-doc and ARM mortgages.

Furthermore, there remains a possibility that, in addition to observable loan and borrower characteristics, OS also cherry-pick loans based on private information unobservable to outsiders. Following common practice in the literature, I use a mortgage's default probability measured over 24 months after origination (early defaults) as an indication of its quality, and examine whether OS loans indeed have lower early default risk. The intuition goes that good loans are likely to survive at least their first two years, while early defaults are often a signal of risky borrowers. The regression model is specified as follows:

$$\Pr\{Early\_default_i\} = \Phi(\alpha + \gamma OS_i + \beta X_i + \mu S_i + \delta_o + \delta_s + \delta_t + \varepsilon_i), \quad (3)$$

where X_i and S_i are loan- and MSA-specific control variables as described earlier, and δ_o, δ_s and δ_t denote three sets of fixed effects for originator, state and default time, respectively. A significantly negative coefficient on OS will provide evidence supporting the postulation that OS loans on average have lower default risks, even after controlling for observable characteristics.

This is indeed the case, as shown in the second column of **Table 2**. For robustness, I also estimate equation (2) and (3) simultaneously to account for potential endogeneity problem and obtain qualitatively similar results. This finding is congruent with Demiroglu & James (2012) who find that loans serviced by their originators have lower ex-post default rate. Together with the previous result, this test confirms that, on average, originators keep lower risk loans in their servicing portfolios based on both observable and unobservable factors. It is thus important to address this selection bias problem before estimating the OS effect on re-default rate in equation (1).

4.2. Identification strategy

While there are no perfect solutions to the endogeneity problem outlined above, due mainly to its unobservability, the quality difference between OS and non-OS mortgages can be alleviated if the regression sample includes only the top quality non-OS loans and the lowest quality OS loans. In order to measure their unobserved quality, I use the time a loan remains in the portfolio of its originator until being securitized. In particular, I select only non-OS loans which were securitized more than 24 months after their origination (hereafter, late securitized mortgages). The rationale is that loans which had performed for at least two years before they were securitized are likely high quality loans. On the other hand, we can reasonably raise questions about the quality of mortgages that were securitized within a few months after their origination, for they are likely risky, conduit-type loans that were originated solely for the purpose of securitization. Thus, I restrict the sample to include only OS loans securitized within 6 months after origination (hereafter, early securitized mortgages).

To the best of my knowledge, this paper is the first to use loan age at securitization as a proxy for loan quality. The lack of prior empirical evidence calls for the following test to justify that there is a link between loan age at securitization and loan quality:

$$\Pr\{Default24_i\} = \Phi(\alpha + \beta Age\_at\_securitization_i + \gamma X_i + \mu S_i + \delta_s + \delta_t + \delta_o + \varepsilon_i). \quad (4)$$

The dependent variable in this model is loan *i*'s probability of default within 24 months following its securitization date, which acts as an ex-post measure of the loan's ex-ante, unobservable quality. The independent variables of interest is *Age_at_securitization*, calculated as the number of months between loan *i*'s origination and securitization dates. The vector of control variables X_i includes loan characteristics as described earlier, and LTV ratio at securitization to account for the possibility that loan age can also be a proxy for the amount of equity accumulation in the property up to that point. S_i includes the change in HPI and unemployment rate in the property's MSA. The usual set of state, time, and originator fixed effects are also included.

In the first column of **Table 3**, the coefficient on the loan age at securitization variable is negatively significant as predicted by my proposition. When a set of dummy variables is used in the second column in place of the continuous age variable, the statistical significance of the coefficients becomes weaker, although their negative signs still indicate lower default probability for older mortgages, with early securitizers (mortgages securitized within 6 months following their origination) serving as the base case for comparison. Notably, the dummy for loan age between 25 and 36 months is both statistically and economically significant.

Although the above evidence suggests that late securitizers are safer than early securitizers in general, in order for my identification strategy to work, I need to confirm that the quality mismatch problem is indeed non-existent or insignificant between late non-OS and early OS loans. Thus, I identify a sample of OS loans less than 6 months old and non-OS loans more than 24 months old at the time of securitization, and estimate the following regression:

$$\Pr\{Default24_i\} = \Phi(\alpha + \beta OS_i + \gamma X_i + \mu S_i + \delta_s + \delta_t + \delta_o + \varepsilon_i). \quad (5)$$

The estimated coefficient of OS is presented in the last column of **Table 3**. In contrast to the results in **Table 2**, OS loans no longer exhibit a lower ex-post default rate compared to non-OS loans, as evidenced by the positive but insignificant coefficient. In summary, the tests presented in **Table 3** justify the use of loan age at securitization as a proxy for unobserved loan quality, and also provide support for the proposition that the quality difference between the two types of loans can be alleviated using this proxy.

Following the selection criteria described above, the final sample used to estimate equation (1) includes 5,358 modified mortgages. Panel C of **Table 1** reports their summary statistics. The new sub-sample has comparable descriptive statistics to the full sample of modified loans shown in Panel B, with the exception of a few variables. It has a more balanced composition of OS and non-OS loans, with each type comprising about half of the sample. Regarding negative equity position, an average borrower in this sub-sample had an outstanding loan balance equivalent to about 72% of his property value at the time he received modification, as compared to 98.84% in the full sample of modified loans. Although the proportion of ARM loans, the average remaining term, and the proportion of loans receiving rate adjustment also differ between the two samples, these differences do not suggest any discernable issues regarding the representativeness of the sub-sample.

5. Empirical results

5.1. Originator-servicers affiliation and loan modification performance

We are now ready to estimate the effectiveness of OS in modifying defaulted mortgages as specified in equation (1). The results are presented in **Table 4**. Our variable of interest *OS* has the expected negative sign. It is both statistically and economically significant across all three horizons

used to measure re-default, but its magnitude decreases as the horizon increases to 12 and 24 months. The magnitude of the coefficients suggest that the probability of re-default within 6 months, 12 months, and 24 months after receiving assistance for OS loans is 29%, 25.6% and 26.5% lower than non-OS loans, respectively. These figures strongly support the presumption that OS are much more effective in performing modification for the loans they originate compared to their counterparts.

Regarding the coefficients on loan characteristics, only negative equity appears to be consistent across the three specifications. Every one percentage point increase in negative equity is associated with a 1.1%, 1.3% and 1.4% increase in the probability of re-default within 6 months, 12 months and 24 months, respectively. ARM loans seem to have higher re-default risk, but it is not statistically significant in the last column. Furthermore, borrowers with longer remaining terms appear less likely to continue making payment, due possibly to lower incentive to hold on to their properties. Turning to the effect of modification type, all four methods have the negative signs as expected, but their statistical significance and magnitude are not stable across the three specifications. On the effect of macro-economic conditions, the two variables measuring movements in the housing and labor markets appear counter-intuitive. As suggested by the coefficients, borrowers in MSAs with higher house prices and lower unemployment rate seem to be more likely to re-default. However, it is important to note that the majority of the modifications in the sample were carried out during the financial crisis (approximately 50% of the sample were modified between 2007 and 2009), amidst very drastic changes in the housing market as well as the economy in general.

Even though the tests in Section 4.2 suggest that using 6-month and 24-month as the thresholds to define early and late securitized loans makes the most empirical sense, one may still

question how sensitive the above results are to the chosen sample. For robustness, I estimate the baseline model again using different samples created by varying the selection criteria as shown in **Table 5**. I focus on the model using the re-default rate within 6 months as the dependent variable, and only the coefficients on *OS* are reported for brevity. In all but the last sample where it becomes statistically weaker at 10% (last row in the last column of **Table 5**), the coefficients are qualitatively similar to the earlier estimates. **Table 5** thus confirms that the difference in the re-default risks between the two types of loans is persistent across different samples.

5.2. Explaining the lower re-default rates of OS loans

This section explores several potential explanations for the superior post-modification performance of OS loans reported in **Table 4** and **Table 5**. Note that using the identification strategy described in the previous section, we can reasonably rule out ex-ante quality as a likely candidate to explain the observed result. The various hypotheses considered in this section belong to two general groups. Those under the first group postulate that OS have stronger incentives than non-OS to allow more substantial modification in hope of avoiding foreclosure, whilst the second group proposes that OS have certain advantages over non-OS, which allow them to better evaluate and select loans for modification. Put differently, the former set of hypotheses posits that OS exert more effort (the "effort" explanations), while according to the latter OS have better capability in performing modification (the "ability" explanations). The tests in all the following sections use the re-default rate within 6 months after modification as the dependent variable, unless otherwise stated.

5.2.1. Effort hypotheses

a. Foreclosure cost

The success of loan modification depends to a great extent on the degree of payment reduction given by lenders. Intuitively, the more concession a borrower receives, the more likely he can continue to make payment, implying that the low re-default rate observed among modified OS loans can simply be a mechanical result of OS giving more substantial payment reduction. This explanation is highly conceivable if OS concentrate their lending in states where it is more costly to foreclose on properties, hence stronger incentives to save defaulted loans. Foreclosure laws differ substantially across U.S. states, which have been both theoretically predicted and empirically tested to affect default behaviors as well as lenders' loss severity (Ambrose, Buttimer, & Capone, 1997; Crawford & Rosenblatt, 1995; Ghent & Kudlyak, 2011). A summary provided in Ghent & Kudlyak (2011) shows that many states forbid deficiency judgments (non-recourse states), such as California or Minnesota, or require a lengthy judicial foreclosure process spanning more than 360 days, such as New York and Michigan, as opposed to just 46 days in Maryland.[13] It follows that in borrower-friendly jurisdictions, lenders or servicers are more inclined to seek alternative loan workouts rather than foreclosure. However, I reject the conjecture that OS have stronger incentives to avoid foreclosure for two reasons. Firstly, the regressions in **Table 4** include state fixed effects, which effectively allows us compare loans within the same state. Secondly, to visually check whether OS loans are indeed disproportionally located in states with high foreclosure costs, I plot the number of OS and non-OS loans in four types of states in **Figure 2**. Following Ghent & Kudlyak (2011), I categorize all states into four types based on whether they have a judicial foreclosure process and allow deficiency judgements. There is no discernable concentration of OS loans in any type of states compared to non-OS loans.

[13] A deficiency judgment allows a lender to pursue the borrower's personal property if the foreclosure sale is not sufficient to cover the mortgage balance due.

b. Reputational concern

Next, reputation can be another potential source of incentives for OS to exert more effort in modifying loans. In their role as servicers, OS may also be wary about their own reputation as originators when handling default cases. For example, if too many foreclosures can damage its name in the mortgage origination business, a servicer may be willing to extend more substantial concessions in order to help borrowers continue to make payment. Using an institution's market share as a proxy for its reputation, I examine if the OS effect changes with reputational costs in **Table 6**. *Top 10 originators* and *Top 10 servicers* are two indicators for ten institutions with the highest market share as originators and servicers, respectively.[14] Arguably, if the low re-default rate of OS loans is driven by reputational concerns, we should observe even stronger negative coefficients for the interaction terms in **Table 6**, but there is no evidence to support this conjecture. Albeit carrying a negative sign, the interaction term *OS*Top 10 originators* is not statistically significant, while the positive coefficient on *OS*Top 10 servicers* is contrary to the prediction by this reputation hypothesis. The coefficients of other controls are suppressed for brevity.

c. Type and extent of modification

More generally, regardless of their motivation, the primary question asked in this section is whether an affiliation with the loan originators causes the servicers to act differently. Thus, I examine the type and extent of modification given by OS and non-OS to look for direct evidence on their willingness to revive the troubled loans. The four types of modification have very different implications for borrowers and mortgage owners. Arrear capitalization is the most commonly used but least helpful for borrowers because it does not reduce their payment burden. Among the

[14] The market share of each institution is calculated using the full sample of mortgages described in Panel A of Table 1.

remaining three options, several theoretical and empirical papers have shown that reducing principal amount is the optimal type of modification, owing to its dual relief effect on payment burden and negative equity for the borrowers (Das & Meadow, 2013; Quercia & Ding, 2009; Goodman et al., 2011a, 2011b; Haughwout et al., 2010). Ambrose & Buttimer (2012) even propose that mortgage contracts should allow for automatic principal adjustment in order to minimize default risk. However, this is the most costly option for the mortgage owners because they have to immediately recognize the loss. On the other hand, Agarwal, Amromin, et al., (2011) find that greater reductions in interest rates are associated with lower re-default rates. There are conflicting findings regarding the effect of extending loan duration on re-default probability, with a positive correlation found in Voicu et al. (2012) and a negative link found in Argawal et al. (2011).

The purpose of the test presented in **Table 7**, however, is not to resolve the debate on which modification method is more effective, but rather to study how effectively OS employ them. The coefficients of interests are the interaction terms between the *OS* dummy and the three type of modification indicators. Note that only 5% of the sample received term adjustment (Panel C of **Table 1**), all of which are non-OS loans, hence the missing interaction term between *OS* and *Adjust term*. Interestingly, the only type of modification that OS appear to have used more effectively is arrear capitalization, but it is the only method that offers no help for borrowers in terms of easing their financial burden.

Finally, an examination of the extent of payment reduction given by OS and non-OS can offer direct evidence on the "effort" conjecture proposed in this section. Since the BBx database only provide information on the type but not the amount of modification, I use the following approach to estimate the payment change for each loan after it was modified. Denote the month a borrower received assistance as time *t*. Using the data on the outstanding loan amount, interest

rate and remaining term at the end of time *t-1*, I recursively calculate the scheduled payments for time *t, t+1* and *t+2*. These are the payments that the borrower would have had to pay for these three months, had they not received any modification at time *t*. The next step involves subtracting the calculated payment for period *t+2* from the actual payment for that month reported by BBx.[15] This difference is the payment change resulting from the modification. As shown in the first row of **Table 8**, the average borrower in my sample received a reduction of about $214.27, which is equivalent to 15.63% of the payment they were originally required to pay. The next two rows report the statistics for OS and non-OS loans separately. In terms of dollar amount, the t-test on the difference in the means of the two groups ($208.4 versus $221.01) is not statistically significant. However, when the change is expressed as a percentage of the borrower's originally required payment, non-OS loans seem to receive a higher concession of 16.98% compared to only 14.46% for OS loans, and the difference is statistically significant. Interestingly, despite having smaller payment reduction, OS loans are found to perform better post-modification. Alongside all the previous evidence presented in this section, this finding essentially implies that the lower re-default rate of OS loans is not attributable to the type and extent of modification the borrowers received. A natural question then follows, is it the result of OS being better at evaluating and selecting borrowers to offer help?

5.2.2. Ability hypotheses

a. Organizational advantages

We now turn to the second strand of hypotheses regarding servicers' ability to perform effective modification. First of all, OS might possess unique characteristics that make them

[15] I do not use the payments at time *t+1* to allow for any possible delays in implementation by the servicers or data reporting by BBx.

inherently better servicers than their counterparts. For example, since all OS must have both loan originating and servicing businesses, they are often big and more diversified institutions, which might imply better servicing capability. In this sense, the OS variable is simply a proxy for size, and all loans serviced by these institutions will have lower re-default probability compared to those serviced by smaller institutions. Although the baseline model in equation (1) already controls for servicer fixed effects, I further test this proposition by re-estimating it using a sample of only those servicers who also have loan origination businesses. If organizational capability is the main driving factor behind the previous finding, we will not observe any significant coefficient on the OS variable in this sub-sample. However, the results reported in **Table 9** do not support this hypothesis. Although its statistical significance and magnitude are weaker than before, the OS coefficients still indicate a considerably lower re-default rate for OS loans. This evidence confirms that a servicer is indeed more effective in modifying the loans it originates than those it does not.

b. Soft information

The above observation leads to the next and final hypothesis that servicers involved in the origination process gain valuable soft information to assist with their subsequent modification decisions. Research on the role of "soft" information has gain increased prominence since the 1990s as the rapid advancement of information technology drastically reduces the need for face-to-face interactions. While there is yet any formal definition of soft information in the literature, it is often associated with being qualitative and personal in nature, as opposed to hard information that can be objectively measured and quantified (Berger & Udell, 2002; Petersen, 2004). Soft information can only be obtained through close, and often repeated, interactions between two or more parties. The consensus in the literature is that such information is beneficial and important

for both lenders and borrowers. As a supplement to hard information, soft information provides lenders with a more precise assessment of borrowers' risk characteristics, therefore improving their credit decision making (Diamond, 1984; Rajan, 1992).[16] Additionally, through building a personal relationship with lenders, not only can borrowers increase their access to credit but also negotiate more favorable terms, especially borrowers whose hard information is difficult to verify (eg., Agarwal & Hauswald, 2010; Berger & Udell, 1995; Petersen & Rajan, 1994). At the retail lending level, Agarwal, Ambrose, Chomsisengphet, & Liu (2011) use data on home equity loans to show that financial institutions do rely on soft information to assess borrowers' risk and determine the appropriate annual percentage rate requirement for them. Conklin (2015) also finds that face-to-face interaction between a mortgage broker and borrower in the loan origination process can help educate borrowers and thus reduce problems associated with financial illiteracy.

Success in loan modification depends largely on the servicers' ability to determine the likelihood that borrowers can continue making payments after their contracts are modified. Essential to this decision is the evaluation of the borrower's characteristics and financial conditions, which requires collecting and assessing information, especially soft information that is often not reflected in their loan documents. Since this is a costly and time-consuming process, the originator of a loan who has already gone through the initial underwriting process will have an advantage over other institutions performing this task. Such information friction can present a major challenge to loan modification for securitized mortgages when servicers are not the loan originators.

[16] However, newer evidence from Petersen & Rajan (2002) indicates that banks were relying increasingly on hard information and impersonal interactions in their lending to small firms from 1973 to 1993. This is attributed to increased labor productivity brought about by advancement in communication technology.

Since soft information is unobservable to outsiders, testing this hypothesis directly is challenging. The following indirect tests are based on its several testable implications. Firstly, an observation that OS are more successful in modifying loans that are informationally opaque, such as low-doc loans, will be consistent with the information hypothesis. However, the estimation of model (1) in **Table 10** does not support this proposition, as shown by the interaction term between *OS* and *Lowdoc*. Secondly, given that they have lower information cost and better information quality to aid with their decision making, OS are expected to be more effective in modifying loans whose success probability is more difficult to assess. In particular, it is much riskier to modify mortgages with negative equity because these borrowers have high propensity to give up their properties. Sorting borrowers in my sample by negative equity position, I find that about 24% of my sample owed more than their house value when they received modification, with the top 10% of borrowers having outstanding loan balance equivalent to more than 117% of their house value. The dummy indicator for borrowers with negative equity, *Negative equity dummy*, is interacted with the *OS* indicator in the second column in **Table 10**. Consistent with the prediction by the information hypothesis, the interaction term is negative and significant at the 5% level, suggesting that OS are especially better at dealing with borrowers with negative equity.

Finally, this hypothesis also implies that useful information about the borrowers obtained in the origination process, if any, should become less relevant as the modification is done further from the origination date. I test this conjecture using a set of dummy variables indicating the loan age at modification in **Table 11**. As predicted, the coefficients of the interaction terms between OS and these dummy variables are positive and monotonically increasing as loan age increases. Interestingly, if the loan is modified more than 48 months after its origination date, there is almost

no difference in the performance of OS versus non-OS. In other words, the positive effect of involvement in loan origination dissipates over time and does not extend beyond 4 years.

To summarize the findings in this section, I find that OS do not possess institutional advantages that lead to their higher success rate in loan modification. Instead, it is likely that they benefit from the original loan underwriting process and are able to use these informational advantages effectively in making later modification decisions.

V. Conclusion

The detachment between originators and the loans they underwrite in mortgage securitization has attracted much attention from researchers, practitioners and policy makers alike. The focus of virtually all discussion thus far is on the lenders' disincentives to carefully screen borrowers in the initial loan origination process, and the asymmetric information problem when these loans are sold to investors. This paper adds to the existing literature by examining whether and how originators also have important advantages over other parties in managing their loans in the long run. More precisely, I compare the success rate in loan modification among MBS servicers when they also act as originators versus when they do not, after controlling for any pre-existing difference in loan quality.

Using a sample of mortgages underlying residential MBS in the U.S., I find that servicers are much more effective in modifying the mortgages originated by themselves. The probability of re-default within 6 months, 12 months and 24 months after receiving modification for OS loans is 29%, 25.6% and 26.5% lower than non-OS loans, respectively. More importantly, further evidence shows that there are no discernible differences in the type and extent of modification given by OS in comparison to their counterparts. Indeed, it is their ability to assess and select the right loans to

modify that drives the result, which likely comes from the soft information collected during the initial underwriting process. This is evidenced in the finding that OS are especially effective in working with mortgages that are often more challenging to evaluate, in particular underwater loans. In addition, the effect tapers off as the modification occurs further from the origination dates and disappears after about four years, consistent with old information being less valuable. However, these observations are limited in that they only offer indirect support for the soft information story. Further research is needed to shed light on this hypothesis. Nevertheless, the findings in this paper raise important questions for practitioners and policy makers concerning about the effectiveness of MBS servicers, as well as servicers of securitized loans in general, in performing important tasks such as loan modification. The cost associated with mortgage securitization is obviously not limited to moral hazard and adverse selection problems at the beginning of the process, but extends throughout the life of the underlying mortgages.

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Figure 1. Distribution of loans by State

This figure plots the number of OS and non-OS loans in four type of states as categorized in Ghent & Kudlyak (2011). *Non-judicial, Recourse* states include AL, CO, DC, GA, HI, ID, MI, MO, MS, NE, NV, NH, OK, RI, TN, TX, UT, VA, WV, and WY. *Judicial, Recourse* states include CT, DE, FL, IL, IN, KS, KY, LA, ME, MD, MA, NJ, NM, NY, OH, PA, SC, SD, and VT. *Non-judicial, Non-recourse* states include AK, AZ, CA, MN, MT, NC, OR, and WA. *Judicial, Non-recourse* states include AR, IA, NC, ND and WI.

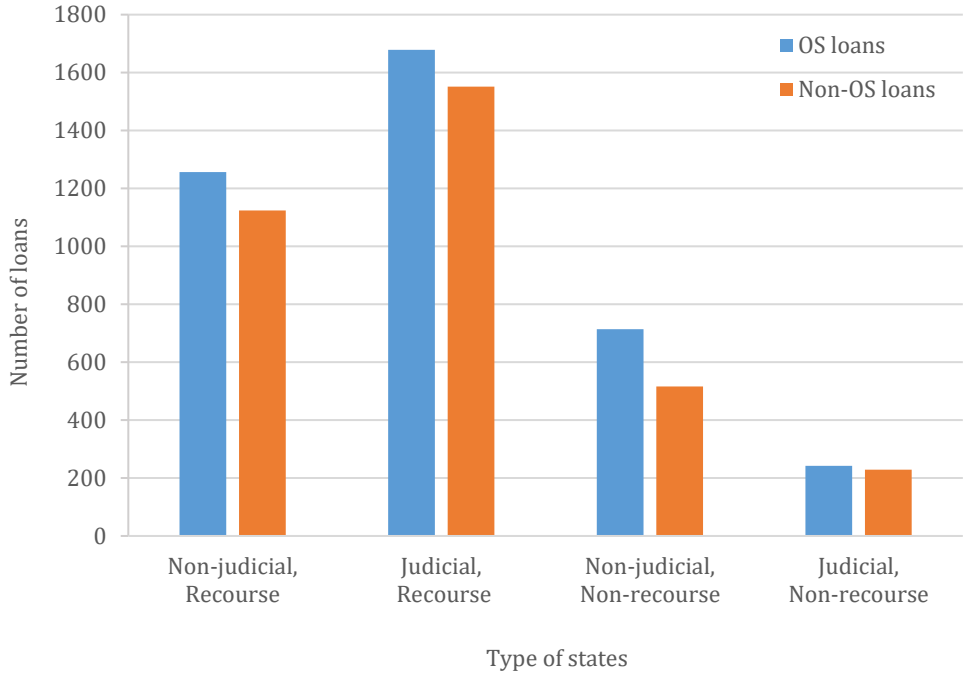

Table 1. Summary statistics

This table reports the summary statistics of all loans in the sample. *OS* is an indicator for a loan originated and serviced by the same institution; *FICO* is the credit score developed by FICO; *Principal* is the original loan amount in USD; *LTV* is the loan-to-value ratio; *Term* is the loan term in months; *Interest rate* is the annual interest rate charged on the loan; *ARM* is dummy for adjustable rate mortgages; *Lowdoc* is a dummy for loans with low or no documentation; *Re-default* is a dummy for a loan that defaults within 24, 12 or 6 months after it is modified, where default is defined as at least 90 days delinquency; *Investment property* is a dummy for a house bought for investment purposes; *Remaining term* is the number of months remaining at the time of modification; *Negative equity* is calculated as the LTV ratio at modification minus one; *Reduce principal* is an indicator for a loan receiving a reduction in outstanding principal; *Adjust rate* is an indicator for a loan receiving an adjustment in interest rate, *Adjust term* is an indicator for a loan receiving an adjustment in loan term; *Capitalize arrears* is an indicator for a loan receiving arrear capitalization.

Variable	Mean	Std. Dev.	Min	Max
Panel A: Full sample (n=532,116)				
OS	0.10	0.29	0	1
FICO	585.39	44.41	500	730
Principal (USD)	197,334	128,292	40,000	647,500
LTV (%)	79.84	12.39	25	100
Term (months)	358.95	35.13	180	480
Interest rate (%)	8.63	2.54	2	16.375
ARM	0.76	0.43	0	1
Lowdoc	0.38	0.48	0	1
Panel B: Sample of modified loans (n=176,961)				
Re-default (24 months)	0.60	0.49	0	1
Re-default (12 months)	0.44	0.50	0	1
Re-default (6 months)	0.23	0.42	0	1
OS	0.03	0.16	0	1
ARM	0.77	0.42	0	1
Lowdoc	0.31	0.46	0	1
Investment property	0.03	0.18	0	1
Remaining term (months)	319.33	42.15	132	480
Negative equity (%)	-1.16	29.56	-90.93	89.45
Reduce principal	0.41	0.49	0	1
Adjust rate	0.79	0.41	0	1
Adjust term	0.01	0.11	0	1
Capitalize arrears	0.83	0.38	0	1
Panel C: Sample of modified loans – Early securitized OS loans and late securitized non-OS loans (n=5,358)				
Re-default (24 months)	0.57	0.49	0	1
Re-default (12 months)	0.42	0.49	0	1
Re-default (6 months)	0.24	0.43	0	1
OS	0.53	0.50	0	1
ARM	0.58	0.49	0	1
Lowdoc	0.33	0.47	0	1
Investment property	0.03	0.17	0	1
Remaining term (months)	300.05	65.42	132	480
Negative equity (%)	-18.08	29.82	-90.9	89.4
Reduce principal	0.35	0.48	0	1
Adjust rate	0.67	0.47	0	1
Adjust term	0.05	0.22	0	1
Capitalize arrears	0.85	0.35	0	1

Table 2. Characteristics of OS loans

This table reports the estimations of equation (2) and (3). *OS* is an indicator for a loan originated and serviced by the same institution; *Early default* is a dummy for a loan that defaults within 24 months after it is originated, where default is defined as at least 90 days delinquency; *FICO* is the credit score developed by FICO; *Principal* is the original loan amount (in log); *LTV* is the loan-to-value ratio; *Term* is the loan term in months; *Interest rate* is the annual interest rate charged on the loan; *ARM* is dummy for adjustable rate mortgages; *Lowdoc* is a dummy for loans with low or no documentation; *Change in HPI* is the change in the FHFA house price index of the MSA where the property is located, calculated from origination to the time the loan defaults; *Change in unemployment rate* is the change in the unemployment rate of the MSA where the property is located, calculated from origination to the time the loan defaults.

VARIABLES	OS	Early default
	(1)	(2)
OS		-1.668***
		(0.023)
FICO	0.002***	-0.001***
	(0.000)	(0.000)
Principal (log)	-0.113***	0.279***
	(0.013)	(0.012)
LTV	-0.007***	0.034***
	(0.001)	(0.001)
Term	-0.002***	0.005***
	(0.000)	(0.000)
Interest rate	-0.014***	0.101***
	(0.002)	(0.003)
ARM	0.118***	-0.233***
	(0.016)	(0.017)
Lowdoc	0.201***	0.289***
	(0.013)	(0.012)
Change in HPI (MSA)		-0.031***
		(0.001)
Change in unemployment rate (MSA)		-0.029***
		(0.000)
Constant	5.366***	-15.281***
	(0.261)	(1.802)
Originator FE	Yes	Yes
State FE	Yes	Yes
Time FE	Yes	Yes
Observations	209,456	209,221
Pseudo R	0.198	0.276

Table 3. Testing the early securitization assumption

This table repoorts the estimation of equation (4) and (5). *Age at securitization* is calculated as the number of months between loan origination and securitization dates. Other control variables include *LTV at securitization*, *Change in HPI (MSA)*, and *Change in unemployment rate (MSA)*. Loan characteristics include *FICO, Principal (log), LTV, Term, Interest rate, ARM,* and *Lowdoc.*

	Default within 24 months after securitization		
VARIABLES	(1)	(2)	(3)
Age at securitization	-0.035**		
	(0.015)		
Dummies for age at securitization:			
6-24 months dummy		-0.039	
		(0.047)	
25-36 months dummy		-0.578**	
		(0.295)	
37-48 months dummy		-0.361	
		(0.497)	
48-60 months dummy		-0.504	
		(0.678)	
> 60 months dummy		-1.195	
		(0.997)	
OS			0.734
			(1.110)
Other controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes
Observations	99,420	99,420	10,317
Pseudo R	0.563	0.572	0.611

Table 4. Re-default probability of modified loans

This table reports the estimation of equation (1). *Re-default* is a dummy for a loan that defaults within 24, 12 or 6 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution; *ARM* is dummy for adjustable rate mortgages; *Lowdoc* is a dummy for loans with low or no documentation; *Investment property* is a dummy for a house bought for investment purposes; *Remaining term* is the number of months remaining at the time of modification; *Negative equity* is calculated as the LTV ratio at modification minus one; *Reduce principal* is an indicator for a loan receiving a reduction in outstanding principal; *Adjust rate* is an indicator for a loan receiving an adjustment in interest rate, *Adjust term* is an indicator for a loan receiving an adjustment in loan term; *Capitalize arrears* is an indicator for a loan receiving arrear capitalization; *Change in HPI* is the change in the FHFA house price index of the MSA where the property is located, calculated from origination to the time the loan defaults; *Change in unemployment rate* is the change in the unemployment rate of the MSA where the property is located, calculated from origination to the time the loan defaults.

	Re-default within		
VARIABLES	6 months	12 months	24 months
OS	-0.343**	-0.296**	-0.307**
	(0.161)	(0.133)	(0.129)
ARM	0.430***	0.156*	0.085
	(0.094)	(0.080)	(0.079)
Lowdoc	0.019	0.015	-0.055
	(0.097)	(0.084)	(0.084)
Investment property	-0.123	-0.193	0.327*
	(0.242)	(0.210)	(0.195)
Remaining term	0.001	0.001*	0.002***
	(0.001)	(0.001)	(0.001)
Negative equity	0.011***	0.013***	0.014***
	(0.002)	(0.002)	(0.002)
Type of modification:			
Reduce principal	-0.600***	-0.217**	-0.097
	(0.111)	(0.088)	(0.085)
Adjust rate	-0.151	-0.351***	-0.481***
	(0.105)	(0.093)	(0.096)
Adjust term	-0.073	-0.199	-0.476**
	(0.241)	(0.213)	(0.211)
Capitalize arrears	-1.381***	-0.663***	-0.403***
	(0.117)	(0.116)	(0.117)
Change in HPI (MSA)	0.059***	0.073***	0.065***
	(0.017)	(0.011)	(0.008)
Change in unemployment rate (MSA)	-0.038***	-0.022***	0.002
	(0.006)	(0.003)	(0.002)
Constant	-0.179	1.647	-2.329**
	(1.385)	(1.334)	(0.976)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes
Observations	4,556	4,577	4,578
Pseudo R	0.155	0.130	0.134

Table 5. Testing the baseline model with different samples of early and late securitized loans

This table reports the coefficients on the *OS* variable obtained from estimating equation (1) for various loan samples. The dependent variable is a loan's re-default rate within 6 months following its modification date. Standards errors are in brackets.

Time between origination and securitization		Early securitized OS loans		
		<= 6 months	<=12months	<=24 months
Late securitized non-OS loans	> 12 months	-0.414***	-0.455***	-
		(0.133)	(0.131)	-
	> 24 months	-0.343**	-0.390**	-0.285*
		(0.161)	(0.157)	(0.153)

Table 6. Re-default probability controlling for originator's and servicer's reputation

This table reports the estimation of equation (1) controlling for originator's and servicer's reputation. *Re-default* is a dummy for a loan that defaults within 6 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution; *Top 10 originators* is an indicator for the ten originators with the highest market share in the sample; *Top 10 servicers* is an indicator for the ten servicers with the highest market share in the sample. Other control variables are listed in equation (1).

VARIABLES	(1)
OS	-1.020**
	(0.415)
OS*Top 10 originators	-0.136
	(0.476)
OS*Top 10 servicers	0.877*
	(0.482)
Other controls	Yes
Time FE	Yes
Servicer FE	Yes
State FE	Yes
Observations	4,921
Pseudo R	0.153

Table 7. Modification type and re-default probability

This table reports the estimation of equation (1) with modification type interaction terms. *Re-default* is a dummy for a loan that defaults within 6 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution; *Reduce principal* is an indicator for a loan receiving a reduction in outstanding principal; *Adjust rate* is an indicator for a loan receiving an adjustment in interest rate, *Adjust term* is an indicator for a loan receiving an adjustment in loan term; *Capitalize arrears* is an indicator for a loan receiving arrear capitalization. Other control variables include all the control variables listed in equation (1).

VARIABLES	Re-default within 6 months
OS	0.249
	(0.290)
OS*Reduce principal	0.202
	(0.214)
OS*Adjust rate	-0.337
	(0.203)
OS*Adjust term	-
OS*Capitalize arrears	-0.487**
	(0.227)
Other controls	Yes
Time FE	Yes
Servicer FE	Yes
State FE	Yes
Observations	4,921
Pseudo R	0.153

Table 8. Extent of modification

This table reports the summary statistics on the amount of payment change as a result of loan modification.

	Payment change ($ amount)		Payment change (% of original payment)	
	Mean	St. Dev.	Mean	St. Dev.
All loans	-214.27	370.54	-15.63%	22.57%
OS loans	-208.40	341.63	-14.46%	19.62%
Non-OS loans	-221.01	401.17	-16.98%	25.48%
t-stat	-1.23		-4.05***	

Table 9. Sample of servicers with loan origination business

This table reports the estimation of equation (1) using the sample of only servicers who also have loan origination business. *Re-default* is a dummy for a loan that defaults within 6, 12 and 24 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution. Other control variables include all the control variables listed in equation (1).

	Re-default within		
VARIABLES	6 months	12 months	24 months
OS	-0.280*	-0.256**	-0.266**
	(0.161)	(0.133)	(0.128)
Other controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Servicer FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	4,029	4,048	4,043
Pseudo R	0.165	0.133	0.136

Table 10. Informational advantages and re-default probability

This table reports the estimation of equation (1) with additional interaction terms. *Re-default* is a dummy for a loan that defaults within 6 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution; *Lowdoc* is a dummy for loans with low or no documentation; *Negative equity indicator* is a dummy for borrower with outstanding balance higher than his house value at the time of modification.Other control variables include all the control variables listed in equation (1).

	Re-default within 6 months	
VARIABLES	(1)	(2)
OS	-0.436**	-0.376**
	(0.173)	(0.174)
OS*Lowdoc	0.280	0.273
	(0.195)	(0.195)
OS*Negative equity dummy		-0.513**
		(0.262)
Other controls	Yes	Yes
Time FE	Yes	Yes
Servicer FE	Yes	Yes
State FE	Yes	Yes
Observations	4,556	4,556
Pseudo R	0.155	0.156

Table 11. Age at modification and re-default probability

This table reports the estimation of equation (1) controlling for loan age at modification. *Re-default* is a dummy for a loan that defaults within 6 months after it is modified, where default is defined as at least 90 days delinquency; *OS* is an indicator for a loan originated and serviced by the same institution; *Loan age at modification* is a set of dummy variables for loan age at securitization, calculated as the number of months between loan origination and modification dates. Other control variables include all control variables listed in equation (1).

VARIABLES	Re-default within 6 months
OS	-12.109***
	(1.424)
OS * Loan age at modification:	
25 – 36 months dummy	11.433***
	(1.474)
37 – 48 months dummy	11.692***
	(1.453)
49 – 60 months dummy	12.070***
	(1.432)
> 60 months dummy	11.957***
	(1.437)
Other controls	Yes
Time FE	Yes
Servicer FE	Yes
State FE	Yes
Observations	4,556
Pseudo R	0.157

Appendix

Table A1. List of top 10 originators and servicers

Panel A. Top 10 originators by number of loans originated			
Originator	Number of loans	Share of sample	Cumulative share
New Century	51,728	9.70%	9.70%
Option One	40,419	7.58%	17.27%
Fremont	36,666	6.87%	24.15%
First Franklin	33,470	6.27%	30.42%
BNC	31,095	5.83%	36.25%
WMC Mortgage	30,032	5.63%	41.88%
Argent	25,948	4.86%	46.75%
Wells Fargo	22,883	4.29%	51.04%
Countrywide Home Loans	16,548	3.10%	54.14%
Resmae Mortgage	11,377	2.13%	56.27%
Panel B. Top 10 servicers by number of loans serviced			
Servicer	Number of loans	Share of sample	Cumulative share
Ocwen	149,796	28.08%	28.08%
Nationstar	55,213	10.35%	38.43%
Wells Fargo	53,889	10.1%	48.53%
JP Morgan Chase	48,570	9.11%	57.64%
Aurora Loan Services	24,330	4.56%	62.20%
Countrywide Home Loans	18,416	3.45%	65.65%
Litton Loan Servicing	16,930	3.17%	68.83%
Ameriquest	16,411	3.08%	71.90%
Select Portfolio Servicing	16,395	3.07%	74.98%
Homeq	13,817	2.59%	77.57%