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REGIME SHIFT AND THE POST-CRISIS WORLD OF MORTGAGE LOSS SEVERITIES

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Abstract

The average loss rate for conventional mortgages rose from less than 10% pre-crisis to more than 30% during the crisis, reaching and sustaining greater than 40% post-crisis. Using a novel database that contains the components of mortgage losses, we identify a regime shift in loss severities caused by various government interventions and changes in business practices in the servicing industry. This regime shift helps explain the persistently high loss severities post-crisis, even after a strong recovery in the housing market. Our findings have implications for loss modeling, pricing, and, potentially, mortgage credit availability.

Regime Shift and the Post-Crisis World of Mortgage Loss Severities

1. Introduction

In the wake of the financial crisis, academics, business practitioners, and policy analysts have sought new insights into, and improved modeling of, mortgage default.[1] However, these studies have focused almost exclusively on only one of the two components of default risk, the probability of default (PD). Mainly because of data limitations, very few studies have analyzed the other major component of default risk, loss-given default (LGD), or loss severity. In this paper, we leverage a newly available dataset from Freddie Mac to study loss severities in the conventional mortgage market from 2000 to the present. Not only does the Freddie Mac data encompass the full boom, bust, and recovery periods surrounding the financial crisis, it also contains detailed information on the components of loss severity. This unique panel provides an opportunity to understand mortgage loss formation during a period of immense economic and regulatory change, the culmination of which is a new post-crisis regime of systematically higher loss severities on mortgage loans.

The average loss severity rate for Freddie Mac loans more than tripled during the crisis and, surprisingly, stayed extraordinarily high in recent years despite a full recovery of the housing market. During the crisis, the rationale for high severity rates was an historic decline in house prices combined with limited capacity to manage an enormous pipeline of defaulted mortgages. While these problems have abated, loss severities remain at record highs, which is a puzzle. In this paper, we solve this puzzle by performing detailed analysis on these loans.

Our loan sample contains more than 15 million fixed-rate mortgages (FRMs) acquired by Freddie Mac between 1999 and 2014, with performance tracked through 2015. Among the loans that defaulted and were liquidated, we have detailed loss information including all the main components of loss. Our main findings are as follows. First, we find that sales recoveries closely track the housing cycle — declining significantly during the crisis and then increasing with the recovery. Second, our regressions and difference-in-differences (DID) tests show that because of various legal and regulatory interventions in the mortgage market, we entered a new regime of

[1] See, e.g., Foote, Gerardi, and Willen (2008); Demyanyk and Van Hemert (2011); Mian and Sufi (2009); Keys et al. (2010); Elul et al. (2010); Agarwal et al. (2014); Campbell and Cocco (2015); and Rajan, Seru, and Vig (2015); An, Deng, and Gabriel (2015); and Fang, Kim, and Li (2016).

prolonged liquidation timelines and increased liquidation expenses starting in 2009. This regime shift, together with the overhang of legacy loans, explains the lingering high loss severities. Because some of these structural breaks appear permanent, it is unlikely that loss severities will revert back to anything close to pre-crisis levels. Higher loss severities and more expensive credit could be the "new norm." Finally, we also find that mortgage insurance (MI) recoveries play an important role in offsetting Freddie Mac loan losses. Because MI companies are becoming more stringent on paying insurance claims, especially with regards to accrued interest and liquidation expense claims, it is likely that loss recoveries from this source will decline.

Our empirical analysis contributes to the academic literature in a number of important ways. This is the first paper to comprehensively investigate the components of loss severity, which we show is important for our understanding of the drivers of loss-severity dynamics.[2] As a result, we fill important gaps in the mortgage LGD literature, which has been unable to study the components of loss severity in a systematic way.

Second, existing LGD studies usually cover only a short timeframe (see, Lekkas, Guigley, and Van Order, 1993; Berkovec, Canner, Gabriel, and Hannan, 1998; Calem and LaCour-Little, 2004; Capozza and Thomson, 2005; and, Qi and Yang, 2009). Our current research covers the complete boom, bust, and recovery cycle surrounding the financial crisis, highlighting critical structural breaks. Toward that end, our findings underscore the importance of model instability in assessing mortgage risk.[3] Recently, Rajan, Seru, and Vig (2015) and An, Deng, and Gabriel (2015) demonstrate that default probability (PD) models can be unstable because of fundamental changes in agent behavior.[4] We add to this literature by showing that structural breaks happened in LGDs. Statistical models that fail to take these changes into account will substantially underestimate losses.

Finally, our LGD model builds on the existing literature and provides important additional findings. For example, we find localized serious delinquency (SDQ) rates contributed significantly

[2] Goodman and Zhu (2015) tabulate loss severities of Freddie Mac loans but do not conduct detailed analysis of loss components.
[3] See, LaCour-Little, Park, and Green (2012) and An et al. (2012) for some initial discussions of model stability in assessing mortgage prepayment and default risks.
[4] Frame, Gerardi, and Willen (2015) also show that models developed without crisis-period data can significantly underestimate the default risk of GSE portfolios.

to higher severity rates. We also find that refinance, and especially cash-out refinance, loans have significantly higher loss severity rates, *ceteris paribus*, likely because of inflated property appraisals at loan origination.

On a practical level, models developed in this paper can help the investment community more accurately estimate losses of Government Sponsored Enterprise[5] (GSE) loans and price GSEs' fast-growing credit risk transfer (CRT) deals.[6] Our models can also be used in stress testing and other applications.

The paper proceeds as follows. In Section 2, we describe our data and document the rise of loss severity rates in the past 15 years. In Section 3, we present our regression analysis, as well as DID tests that help identify structural breaks in loss formation. Conclusions and areas for future work discussed are in Section 4.

2. The Default Process, Data, and Loss-Severity Trends

2.1. Background information on the default process and loss formation

Figure 1 depicts the typical mortgage default process, which will help us understand how mortgage losses are formed. Delinquency starts when borrowers stop paying their loans. Typically, around the 45th day of delinquency, a notice of default is issued to the borrower, which starts the foreclosure process.[7] This ceases if the borrower makes the associated back payments and late fees.

Borrowers are usually given some time to cure the default, but if the loan remains in delinquency after a certain period of time, the investor, usually through the servicer, starts the foreclosure process. In judicial-foreclosure states, investors need to file a request with the court in order to sell the property to recover their debts (see, e.g., Brueggeman and Fisher, 2015; Gerardi, Lambie-Hanson, and Willen, 2013).[8] In non-judicial states, the mortgage servicer hires a local attorney

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[5] The two GSEs are Fannie Mae and Freddie Mac

[6] By the end of the first quarter of 2016, the two GSEs had issued about $30 billion of CRT bonds referencing to more than $1 trillion of GSE pool balances. In these deals, the GSEs give up some of their guarantee fee to transfer some of their default risk to private investors.

[7] In the Consumer Financial Protection Bureau (CFPB) servicing rules, which took effect in 2014, lenders are required to send delinquent borrowers written notice no later than the 45th day of delinquency. But lenders cannot initiate foreclosure until after the 120th day.

[8] Twenty-two states are judicial foreclosure states. The District of Columbia and 28 states are nonjudicial states.

who schedules a foreclosure auction, hires an auctioneer, and issues notices to the borrower and the public (usually in the form of newspaper ads) leading up to the auction. The auction concludes the foreclosure process, and through it the ownership rights are transferred from the defaulting borrower to the mortgage investor. As we will show, the foreclosure process can be very lengthy, especially in judicial states and especially in recent years.

Given the time and costs involved in foreclosure, some investors prefer to pursue a different option, which is a loan modification (Ambrose and Capone, 1996).[9] Absent that, another way of reducing expenses is to conduct a short sale, which happens when borrowers agree to find a third-party buyer, effectively shortening the foreclosure process. But a short sale results in a shortfall (sales proceeds not able to cover the unpaid balance), and the losses are borne by the lender or shared by the lender and the borrower. Another foreclosure alternative, a deed in lieu of foreclosure, occurs when borrowers voluntarily surrender the title of the property to the lender, again shortening the foreclosure process.

If the foreclosure cannot be averted, a foreclosure sale takes place. In some cases, the property can be sold to a third party, at which point loss claims are settled.[10] Absent a third-party sale, the investor takes over the property, and it becomes real estate owned (REO). The lender can subsequently pursue a sale of the property (REO sale), which typically results in losses to the lender. If the investor believes no recoveries can be made, the loan can be charged off, ending the liquidation process.[11]

The complicated default process described above is designed to maximize recoveries on properties that are involuntarily terminated, thus minimizing losses on defaulted loans. Because sales proceeds largely depend on conditions in local real estate markets, recoveries are time varying and highly uncertain. In addition, the loan liquidation process is a lengthy process involving many expenses, making liquidation expenses an increasingly large driver of losses, as we will see.

[9] Certain programs, such as the Home Affordable Modification Program (HAMP), use government subsidies to help borrowers get loan modifications. See Agarwal et al. (2013) for an in-depth analysis of HAMP.
[10] In recourse states, investors can in theory reduce losses through the pursuit of a deficiency judgment (Ghent and Kudlyak, 2011).
[11] This became an increasingly common practice during the crisis, as many properties became "tax foreclosures" and ultimately owned by the local taxing jurisdictions.

Another way to minimize losses is through private mortgage insurance (PMI). Indeed, some form of credit enhancement is required by the GSEs for all loans with less than a 20% down payment, with borrower-paid MI by far the most common.[12] Freddie Mac can also reduce losses through non-MI recoveries, which most often happens when lenders are required to repurchase loans that have underwriting defects. At times, they can also get other non-MI recoveries, including tax refunds, rental receipts, and escrow refunds.

2.2. Loan loss data and other data

To promote its CRT deals, starting in 2014 Freddie Mac began releasing to the public detailed loan-level loss data on their first-lien, full-documentation, FRM loans originated starting in 1999. We obtained these data directly from the Freddie Mac website.[13] We also obtained supplemental data to help in our modeling, including market interest rates; the CoreLogic zip code–level house price index (HPI); Bureau of Labor Statistics (BLS) county-level unemployment rates; mortgage performance information from a third source, McDash Analytics; and, finally, servicer merger and acquisition (M&A) data from various sources. They are all matched with our mortgage data for modeling in the ways described below.

Loss information is available for loans liquidated through property disposition via either a conventional REO disposition or one of the foreclosure alternatives in Figure 1.[14] Our final mortgage loss sample contains 339,217 loans that were originated between 1999 and 2013 and liquidated from 2000 to 2015.[15] The loss information includes loan liquidation date, type of liquidation, default unpaid principal balance (UPB), liquidation expenses, net sale proceeds,[16] MI recoveries and non-MI recoveries.

In addition to loan loss information, the Freddie Mac data provide detailed information on loan characteristics, including original and current principal balance, note rate, loan-to-value (LTV)

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[12] Lender-paid MI also occurs and can be set up to mimic borrower-paid MI. Pool-insurance policies are another form of MI but are not as common.
[13] See http://www.freddiemac.com/news/finance/sf_loanlevel_dataset.html.
[14] The full credit performance dataset released by Freddie Mac contains more than 17 million loans. Some bad data and outliers are excluded from our analysis.
[15] We exclude the 2014 vintage from our analysis to avoid a potential problem of loss recovery understatement in the data caused by recovery delays.
[16] Selling expenses are subtracted from gross sales proceeds to derive net sale proceeds.

ratio and combined LTV at origination,[17] borrower origination FICO score, loan purpose, property occupancy status, MI coverage percentage, the three-digit property zip code,[18] the name of the servicer, and the name of the seller. The Freddie Mac data also contains hundreds of millions of monthly performance records on all loans, including their payment and delinquency status and the ultimate disposition type (voluntary repayment, REO, or foreclosure alternative).[19] The event-history data allow us to identify the whole default timeline, calculate the equity position of each liquidated loan through its entire life, and calculate other time-varying variables.

2.3. Rise in loss severities

We define the loss severity rate as the total net loss divided by the UPB at liquidation, in which total net loss includes net sales losses (net sale proceeds minus UPB), carrying costs and liquidation expenses offset by MI, and non-MI recoveries. Therefore,

$$\text{loss severity rate} = \frac{UPB + carrying\ costs + expenses - sales - MIrecov - nonMIrecov}{UPB} \quad (1).$$

As shown in Table 1, loss severities of Freddie Mac loans have a mean of 42% and a standard deviation of 32%, showing a huge variation ranging from -13% to 122%. A negative loss severity means that Freddie Mac's recoveries exceeded its liquidation costs, and Freddie Mac was able to liquidate those loans with gains.[20] For some loans, loss severity is over 100%, often when the loan is charged off and no recoveries occur on the property. This can also happen if a lengthy process of liquidation results in significant carrying costs and liquidation expenses. In fact, the average time from SDQ to liquidation is about 18 months; nearly 10% of the loans were liquidated three years after becoming seriously delinquent.Net sale proceeds are on average 60% of the UPB. A quarter of the time, sales recoveries are less than 40%. Average liquidation expenses are about 12% of UPB; in some cases, they amount to as much as 48%. The average MI recovery is 22% of

[17] Combined LTV includes all liens at origination. It does not include liens purchased after origination.
[18] Because of privacy concerns, Freddie Mac does not provide the five-digit zip code. The SEC only provides a 2-digit zip code as part of the new Regulation ABII asset-level disclosures.
[19] Freddie Mac lumps short sales, short payoffs, deeds-in-lieu of foreclosure, and foreclosure sales together.
[20] In short sales or foreclosure sales, any extra money after UPB and allowable expenses is required to be returned to the borrower, but in REO sales, these can be retained as Freddie Mac obtains full ownership of the property before property disposition. In some cases, MI recoveries exceed actual losses if the REO occurs more than 60 days after the "claim perfected date" and the MI pays the full claim that more than covers the loss.

UPB for loans with MI. Non-MI recoveries average around 3%. We calculate carrying costs in two parts: the first part is the interest cost in the first four months the servicer advances principal and interest to investors, which gets reimbursed to the servicer; the second part is Freddie Mac's carrying cost after the loan is removed from the MBS pool and placed onto Freddie Mac's balance sheet.[21] Carrying costs are on average about 4% of UPB but have been much lower in recent years.

In Figure 2, we plot average loss severity rates of Freddie Mac loans by year of liquidation. In the same chart, we show the SDQ rate of prime FRM loans based on data from the Mortgage Bankers Association. From 2000 to 2004, loss severity rates are very low, less than 10%. Starting from 2005, severity rate rose significantly, from 14% in 2005 to 22% by 2007. The timing of this severity rate increase is interesting because the national housing market did not turn down significantly until 2007, with SDQ rates remaining low through 2007. This is not surprising when you consider that we observe loss severities only on loans that defaulted. Loans that went through default and liquidation before 2008 were most likely problem loans in areas that did not experience the house price gains in other areas.[22] The sharp rise in loss severities from 2007 to 2010 is clearly related to the sharp decline in house prices nationally during that period. Rising loss severities are also attributed to the sharp rise in delinquent loans, also shown in Figure 2, which overwhelmed mortgage servicing resources and court dockets in some judicial states.

What is most surprising is the high loss severities post-2012, a period when house prices started increasing and delinquencies declined substantially. Loss severities remained over 40% in 2013 before reaching new highs of 45% in 2014 and 44% in 2015. The persistently high loss severity rates post-crisis are in sharp contrast to the decline in SDQ rates that started in 2011. If the rationale for the high loss severity rates during the crisis was historic declines in house prices and limited servicer capacity to manage surging delinquencies, the historically high loss severities that have persisted since 2011 is a puzzle.

[21] GSE practice is to remove loans from securities pools after 120 days of delinquency and then bring them on balance sheet. For the first part of carrying cost, the interest rate is the mortgage note rate minus the guarantee fee, and for the second part, the interest rate is Freddie Mac's cost of funds, which is approximated by the interest rate of Freddie Mac's shorter term senior debt, obtained from the SNL Securities database. Thus, the carrying cost is the accrued interest on the loans for the first four months of delinquency and the Freddie Mac cost of funds from month five through termination when the loan is on its balance sheet.

[22] Michigan and Ohio were the two top states with defaulted loans in the mid-2000s; California was the top state after 2009.

One might think that the high loss severities post-crisis could be due to the large volume of legacy loans whose liquidations were delayed because of various moratoria and the freezing of foreclosures during the "robo-signing" scandal.[23] In other words, there might be a vintage effect. Therefore, in Figure 3, we separate loans by vintage to see whether the aforementioned loss severity trend holds in each loan cohort. From the dashed lines, we see that across all vintages shown in the chart, average loss severity rates grew significantly over time, and the contours are similar to that of all vintages combined (the solid line) — basically a steady growth all the way to the recovery period.

An advantage in analyzing the drivers of these observed loss dynamics in the Freddie Mac data is that it provides detailed information on the components of loss severity. In Figure 4, we plot the two largest loss components, net sales recoveries and liquidation expenses, by year of liquidation. The cyclicality of net sales recoveries is clearly evidenced in the figure, coinciding with the ups and downs of house prices surrounding the financial crisis. What is striking is the increase in expenses in recent years — they rose to 13% in 2013 and 17% in 2014. In contrast, they were as low as 6% as late as 2009 and 2010.

During the foreclosure process, servicers and Freddie Mac incur all kinds of expenses, from loan workout trial expenses to tax and insurance payments to property maintenance and preservation costs. A number of these expenses are time related. In Figure 5, we show the average liquidation timeline of loans liquidated at different times. The dashed lines show loans in judicial and nonjudicial states, respectively, and the solid line shows all loans combined. The longer timelines in judicial states is a result of state laws that require judicial review before liquidation, adding to liquidation timelines. Clearly, the average liquidation timelines for loans liquidated during 2012 to 2015 are significantly higher, especially in judicial states. We will take this pattern into consideration in our subsequent analysis.

[23] These events are described in detail below.

3. Regime Shifts in Loss Severities

In addition to the housing market cycle and liquidation timelines, many factors come into play affecting loss severities. In this section, we conduct in-depth multivariate analysis using our loan-level data.

3.1. Loss severity rate and foreclosure timeline models

At the loan level, we estimate the following linear regression for loss severity rates with potential heteroskedasticity and clustered standard errors:

$$y_i = \alpha + X_{it}\beta + Z_i\gamma + \varepsilon_{ij} \tag{2}$$

where y_i is the loss severity rate of loan i that is liquidated at time t. X_{it} is a vector of factors that are related to time, including foreclosure timelines, the equity position of the property at liquidation, and housing market conditions at the time of liquidation. Z_i is a vector of non–time-varying factors, including liquidation type, dummy variables to capture the legal environment, servicer-fixed effects, and various borrower- and loan-level characteristics. Finally, ε_{ij} is the heteroskedastic disturbance of loan i clustered by group j. We use the reciprocal of UPB at liquidation as a weight in the generalized least squares (GLS) estimation given the concern that the loss severity rate might be very noisy for small UPB loans. We also assume clustering at the state level, so a two-stage GLS is used in parameter estimation.

Our model specification builds on the existing literature (see, e.g., Calem and LaCour-Little, 2004; Qi and Yang, 2009) and incorporates a number of model enhancements. Key variables included are contemporaneous (mark-to-market) LTV, zip code–level serious delinquency rates, foreclosure pipeline volume, liquidation timelines, and the timing of liquidation.

Contemporaneous LTV (CLTV) is included to measure the equity position of the property at liquidation because it largely determines how much net recoveries investors get from the property sale.[24] Zip code–level serious delinquency rates are included to measure market distress; recent

[24] To construct CLTV, we use the zip code–level index from CoreLogic and bring the original LTV current by adjusting the LTV for the change in local HPI. As explained previously, the Freddie Mac data only provided three-digit zip codes, so we had to aggregate the five-digit zip code-level HPI to the three-digit level.

literature finds significant discounts for forced sales (see, e.g., Campbell et al., 2011).[25] State-level foreclosure pipeline volume is meant to capture the effect of court and servicing capacity constraints and congestion. Liquidation timelines capture a large portion of the variation in liquidation expenses. Liquidation timing matters as the defaulted loans might have been exposed to a different market environment in 2015 than in 2005.

The age of the loan at SDQ captures the seasoning effect. Loan characteristics include the size of the loan (log loan balance), original LTV buckets, loan purpose, property occupancy status, and MI coverage percentage.[26] Borrower FICO score at origination is also included. We include the type of liquidation, that is, whether the loan is a foreclosure alternative (short sale, deed in lieu of foreclosure, or third-party sales)[27] or a REO sale. REO sales not only mean longer default timelines but could also be associated with extra property damage (Lambie-Hanson, 2015).

We include vintage-fixed effects. One explanation of the high loss severities in recent years is the so-called "legacy loan overhang." In this regard, the CLTV, liquidation timeline, and other loan and borrower characteristics included in our model should capture the bulk of the "overhang" effect. Any remaining legacy loan effects due to unobserved underwriting impacts should be captured by our vintage dummies.

Finally, servicer-fixed effects and state-fixed effects are included to account for potential differences in liquidation efficiency across servicers and different legal environments across states, respectively. For servicer-fixed effects, we have to standardize servicer names and take into consideration M&As in the servicing industry, as the mortgage servicing industry has gone through substantial M&A activity in the past 15 years. To do this, we manually collect mortgage servicer M&A data and identify the current servicer of each loan at the time of loan liquidation.

In Table 2, we provide summary statistics of the variables used in our regression. Some key statistics are as follows: LTV is close to 100%, the average liquidation timeline is about 18 months,

[25] Zip code SDQ rate is calculated based on the McDash Analytics data, which cover data from the entire market from the top servicers.
[26] We also test the impact of second liens as the existing literature finds that they present an extra hurdle for foreclosure or foreclosure alternatives (Agarwal et al., 2014).
[27] Unfortunately, the Freddie data do not break out different types of foreclosure alternatives.

69% of the liquidations are REO liquidations, about 41% of the liquidated loans are in judicial states, and 60% of liquidated loans were serviced by the top five servicers.

We report our main regression results in Table 3 and include the full model results in Appendix Table 1. We have two different model specifications, the difference being whether or not we include liquidation timelines. We want to see the impact of liquidation timelines on the coefficients of other variables. From the results of both specifications, we see CLTV is a significant determinant of loss severity — the higher the CLTV, the higher the severity, consistent with findings in the existing literature (see Pennington-Cross, 2003; Calem and LaCour-Little, 2004; Qi and Yang, 2009). The zip code–level serious delinquency rates, a proxy for local housing market distress, are also significant in determining loss severities. The higher the delinquency rate in a local area, the higher the loss severity. Results in Table 3 also suggest that foreclosure pipeline volume is capturing some effects of court or servicer capacity constraints and congestion — the larger the number of loans in the foreclosure pipeline, the higher the loss severities.

Related to our earlier observation that loss severities have been surprisingly high post-crisis, we find significant timing effects of liquidation. As we see under model 1, without controlling for individual loan liquidation timelines, loans liquidated from 2009 to 2012 have a five percentage point higher loss severity rate than those liquidated before 2009, *ceteris paribus*. Loans liquidated from 2012 to 2014 have 12 percentage point higher loss severity rates, and those liquidated post-2014 have the highest loss severity rates — 22 percentage points higher than those liquidated before 2009. Note that these effects are after controlling for CLTV, market distress, foreclosure pipeline congestion, vintage-fixed effects, and many loan and borrower characteristics.

As discussed in Section 2, recent liquidations have significantly longer timelines, which could partially explain the higher post-crisis loss severity rates. This is exactly what we see in the results from model 2. We see that liquidation timelines are a strong driver of loss severity.[28] However, after controlling for liquidation timelines, we still see significant effects associated with 2012 to 2014 and post-2014 liquidations, although the effects are much smaller. These results suggest that

[28] The relation is nonlinear, as evidenced in the significance of the spline functions. As an alternative to spline functions, we experimented with polynomial terms. The results are the same.

there are at least two factors related to the high post-crisis loss severities: the prolonged liquidation timelines in recent years and increased non–time-related, or fixed, liquidation costs.

In addition to running the regressions with the full sample, we also run the regressions with non-MI loans only. This is to keep our severity analysis separated from MI recoveries. The last two columns of Table 3 report the non-MI sample results. We see that the results pertinent to liquidation timing remain largely unchanged, suggesting that the increased loss severity rates post-crisis is not likely because of significant changes in MI recoveries. However, we do see that the post-crisis effects are slightly smaller; for example, the post-2014 effect changes from 12 percentage points (model 2, full sample) to 11 percentage points (model 2, non-MI subsample) after we completely remove the impact of MI recoveries. This is consistent with our observation in the data that, post-crisis, MI companies' applied more severe haircuts on GSEs' MI claims on accrued interest and liquidation expenses (see Appendix Figure 1), which slightly increases loss severities of the sample of loans that include MI loans.

Results of other control variables are consistent with findings in the existing literature or economic intuition. For example, we find that cash-out and rate and term refinance loans have higher loss severities, *ceteris paribus*. This is consistent with findings of appraisal bias, more specifically property value inflation in refinance loans, especially where equity is extracted (see Agarwal, Ben-David, and Yao, 2015). Compared to foreclosure alternatives, REO sales result in higher loss severities, even after controlling for liquidation timelines.[29] Increases in MI coverage are associated with decreases in loss severity rates. Loans with original LTVs below 65% have lower loss severities. Second homes and investment properties, collectively referred to as non–owner-occupied loans, have higher loss severities. Higher FICO scores are associated with lower loss severities.[30]

[29] Foreclosure alternatives in general involve some cooperation from borrowers that serves to lower losses. See Ambrose and Capone (1996) for a discussion of the costs and benefits of foreclosure alternatives.

[30] One possible explanation is that borrowers with higher FICO scores are more willing to cooperate in the loan liquidation process because of their stronger concerns for damages to credit, lowering liquidation expenses. Related to this, Berkovec et al. (1998) find that certain borrower characteristics such as marital status are significant in predicting residential mortgage LGD.

In terms of model fit, the adjusted R-squared of our models are over 50%. This is significantly higher than those in Lekkas, Guigley, and Van Order (1993) and Calem and LaCour-Little (2004), which are also based on GSE data.[31]

We also estimate a set of foreclosure timeline models to test how liquidation timing affects foreclosure timelines specifically. The model is an accelerated failure time model similar to that in Cordell et al. (2015). A key issue addressed with this model is the censoring of timelines for loans that recently went into delinquency. For this purpose, we expand our sample to include all loans that are 90 or more days delinquent at the end of our sample period to include censored observations not yet defaulted. Our failure time model is able to capture the censoring effect.

We present our main timeline model results in Table 4 and report the full model results in Appendix Table 2. Given our purpose, we focus our discussion on the liquidation timing effects. As we see in Table 4, we divide our whole study period into 6 sub-periods. In our model, pre-February 2007 is the reference period, the period from February 2007 to October 2008 marks the crisis, and November 2008 to August 2010 marks GSE foreclosure moratoria. We see from Table 4 that after controlling for housing market conditions, the foreclosure pipeline, and other loan and borrower characteristics, foreclosure timelines have increased over time, especially in the post-crisis periods. Note that the coefficients on the timing dummies are largest for loans that became seriously delinquent in the two most recent periods, periods driven by recent legal and regulatory changes, namely the National Mortgage Settlement (NMS) and new CFPB servicing rules. We now turn our attention to estimating the effects of these changes.

3.2. Regime shift difference-in-differences (DID) tests

Regression analyses in Section 3.1 suggest that post-crisis liquidation timelines lengthened and fixed-liquidation costs increased, causing loss severities to remain on a plateau even though the housing market has fully recovered. In this section, we investigate the causes of the extension of foreclosure timelines and increases in liquidation costs post-crisis.

There are a number of reasons why we see prolonged liquidation timelines post-crisis, especially in judicial states. First, there are many legacy loans coming principally from various moratoria and

[31] The R-squared in Lekkas, Guigley, and Van Order (1993) is 6% to 7%, and that in Calem and LaCour-Little (2004) is 25%.

the "robo-signing" scandal in 2010 that resulted in the freezing of foreclosures. We observe from the Freddie Mac data that delinquent loans subject to the GSE moratoria starting in November 2008 on average have a liquidation timeline five months longer than those liquidated before the GSE moratoria.[32]

Second, the loan servicing industry has gone through substantial changes post-crisis, especially after the breakout of the robo-signing scandal in September 2010. Cordell et al. (2015) and Cordell and Lambie-Hanson (2016) document some regime shifts in the servicing industry and the resulting prolonged liquidation timelines.[33] Two important national legal remedies stand out. First, the NMS announced in March 2012 not only required the five largest mortgage servicers[34] in the country to pay out cash compensations to some of the borrowers they serviced, but it also required them to comply with new servicing standards, especially in their handling of delinquent loans.[35] In January 2013, the CFPB announced new servicing rules to take effect a year later in January 2014. Those changes resulted in more loan modifications but also, as we will see, increased liquidation timelines.

One issue with the two aforementioned studies is that they base their claims of regime shifts on time dummies and inspection of the data, not statistical inference. To test empirically their claim of regime shifts in foreclosure timelines in our context, and, more important, impacts on loss severities, we conduct a number of formal tests.

We conduct our tests in a DID framework so that we can be more comfortable drawing conclusions about causal effects than with other approaches. Our DID tests are on both foreclosure timelines and on the overall loss severity rates.

The DID tests are in the standard form:

[32] These loans include loans that were delinquent in November 2008 when the GSE moratoria commenced and all loans delinquent after 2008 up to the point of the robo-signing scandal, when an entirely new event occurred, resulting in the outright freezing of foreclosures at the largest servicers.
[33] These papers use the McDash Analytics data that covers all loans serviced by the top 10 mortgage servicers from 2005 to 2014.
[34] The five largest mortgage servicers are Ally, Bank of America, JPMorgan Chase, Citi, and Wells Fargo.
[35] Later there were a series of additional settlements, such as the Ocwen Settlement (December 2013) and the National Suntrust Settlement (January 2016).

$$y = \alpha + \beta_1 T + \beta_2 P + \beta_3 T \cdot P + W\gamma + \varepsilon \quad (3)$$

where y is foreclosure timelines (in log) or loss severity rate of a loan; T represents the treatment group, which are loans targeted by a new policy or affected by an event; P represents post-treatment, which is the period after policy implementation or event occurrence; W is the vector of control variables; and ε is the error term. Here β_1 captures the generic difference between the treatment group and the control group that is not related to time; β_2 captures the general time trend that applies to both the treatment group and the control group; and β_3 captures the treatment effect, which can be interpreted as the impact of the policy or event.

The two events we test are the NMS and the new CFPB servicing rules, whose rules constitute the new regime for mortgage servicing. In the NMS, a comprehensive set of servicing rules (more than 300 rules) were introduced, which we hypothesize both lengthened foreclosure timelines and increased fixed costs in loan servicing. For example, the NMS required that servicers must evaluate borrowers for all available loan modification options before referring borrowers to foreclosure. It also required that servicers may not proceed with foreclosure sales while an appeal of the denial of a loan modification is pending. The NMS also limited fees that a servicer can collect from a defaulted borrower. The CFPB servicing rules incorporated the NMS rules and added some additional rules. For example, under the CFPB rules, servicers cannot start the foreclosure process on owner-occupied property loans until the 120th day of delinquency, replacing the old standard of 75 to 90 days (sooner for properties found vacated). On the cost side, the CFPB rules require a servicing employee be assigned no later than the 45th day of delinquency, with that employee becoming a "single point of contact" for the borrower while the loan is delinquent, tightening the initial rules in the NMS.[36] Previously, no such rule existed.

Only owner-occupied property loans, not investment properties, are the target of the NMS and CFPB rules, which provides an opportunity to establish a treatment group and a control group. In addition, the NMS rules applied principally to the "Big 5" servicers (Ally, Bank of America, JPMorgan Chase, Citi and Wells Fargo) under the settlement, while the CFPB rules generally

[36] See National Housing Resource Center, "Understanding the National Mortgage Settlement," June 2013 and Bureau of CFPB, "Amendments to the 2013 Mortgage Rules under the Real Estate Settlement Procedures Act (Regulation X) and the Truth in Lending Act (Regulation Z)", 2016.

apply to all servicers, only exempting very small servicers from certain requirements.[37] The NMS was announced in March 2012, with a date of October 2, 2012, to be in full compliance with its 304 servicing standards. The CFPB's servicing rules were announced in January 2013, with an effective date January 2014. Thus, we pick October 2012 and January 2014 as the event dates for our NMS and CFPB tests, respectively.

Table 5 presents our DID test results on foreclosure timelines. In panel A, we use owner-occupied property loans as the treatment group and investment properties as the control group. Because the robo-signing scandal and subsequent NMS were mainly the result of the Big 5 Servicers failing to file proper documentation with courts, it applied principally to defaulted loans of the Big 5 Servicers in judicial states, so we focus these tests on judicial states. To avoid confounding effects of other events, we limit our test window. For the NMS test, the test window goes from September 2010, which is the start of the robo-signing scandal, to January 2014, which is the effective date of the new CFPB servicing rules. Recall the NMS event date is October 2012. Therefore, we limit the pre-event loans, which are our control group, to those that were liquidated between September 2010 and October 2012, and post-event loans are those that were liquidated between October 2012 and January 2014. Furthermore, we carve out from our sample loans that fell into delinquency before October 2012 but were liquidated after October 2012 because they were exposed to both the pre- and post-event environment. Therefore, in panel A, our treatment group affected by the NMS rules is owner-occupied property loans in judicial states that were serviced by the Big 5 Servicers and exposed to the post-NMS environment. For the CFPB test, we limit our test window to be from October 2012 to September 2015 with the event date January 2014.

In panel B, we use delinquent loans serviced by the Big 5 Servicers as the treatment group and those serviced by smaller servicers as the control group. Following the same logic of panel A, to avoid confounding effects, we now limit our tests to owner-occupied property loans in judicial states.

Results in the first column of Table 5, panel A suggest that although there is a general trend of longer foreclosure timelines post-NMS (the significant and positive coefficient of *Post-event* of 0.278), the treatment group has a larger increase in foreclosure timelines post-NMS than the

[37] Small servicers are defined as those that service 5,000 or fewer loans that they or an affiliate service.

control group (the significant and positive coefficient of *Owner* × *Post-event* of 0.264). We take this DID result as evidence that the NMS had a causal impact on foreclosure timelines. Similarly, we see from the second column that there is a general trend of longer foreclosure timelines post-CFPB because the treatment group was more affected (the significant 0.231 coefficient).

Results in the first column of panel B tell a similar story: post-NMS, the treatment group, loans serviced by the Big 5 Servicers, had higher increases in foreclosure timelines than the control group, loans serviced by smaller servicers. This is shown by the significant and positive coefficient of 0.136 on our treatment group of owner-occupied property loans at the Big 5 Servicers. This is again evidence of a causal impact of NMS on foreclosure timelines.

The results in the second column of Table 5, panel B are also of interest. We see again that there is a general trend of longer foreclosure timelines post-CFPB (significant and positive coefficient of *Post-event* of 0.625). Loans serviced by the Big 5 Servicers, which are the treatment group in the NMS period, have shorter changes in timelines post-CFPB than loans serviced by smaller servicers (the significant and negative coefficient of *Big 5 Servicer* × *Post-event* of -0.118). [38] Note that in this case the smaller servicers effectively *become* the treatment group because they are the ones now most affected by the new servicing rules. This is also consistent with the hypothesis that the new CFPB servicing rules had a causal impact on foreclosure timelines beyond the general trend captured by Post-event coefficient of 0.625. The logic is as follows: if the implementation of the CFPB servicing rules represents a shock to servicers, it is more of a shock to smaller servicers other than the Big 5 Servicers, which had already implemented the NMS rules in 2012. As pointed out, because the CFPB rules built on the NMS rules, we hypothesize that the CFPB servicing rules have limited incremental impact on the Big 5 Servicers. In contrast, the rules should have a much larger impact on the smaller servicers because they were not required to adopt the new rules before January 2014. This is exactly what we see in the second column of Table 5 panel B with the negative coefficient on the Big 5 Servicers.

After identifying the causal impact of NMS and CFPB on longer foreclosure timelines, we move to test their impacts on loss severity rates, controlling for foreclosure timelines. Table 6 presents our DID test results. The DID tests in Table 6 are set up exactly the same as those in Table 5,

[38] Two non-NMS servicers, Ocwen (March 2014) and Suntrust (September 2014), engaged in separate settlements and thus are excluded from this sample.

except that now the dependent variable is the loss severity rate, and foreclosure timelines is now an independent control variable.

Results in the first column of Table 6, panel A suggest that although there is a general trend of increased loss severities post-NMS, we see a higher increase in loss severities in the treatment group than in the control group. These results are consistent with the hypothesis that NMS had a causal impact on liquidation expenses that are not related to foreclosure timelines, mainly fixed liquidation expenses. In the second column, we find the DID result to be marginally significant. Results in panel B of Table 6 are also very interesting and reflect an important difference between how much servicers can pass foreclosure *timeline-related* costs to Freddie Mac versus how much they can pass *non–timeline-related* costs to Freddie Mac. We believe servicers can easily do the former but not the latter. This is because non–timeline-related costs are largely overhead G&A costs, which are not reimbursable. Individual servicers cannot easily pass non–timeline-related costs to Freddie Mac.[39] Reflected in the results in column 1, we do not see a significant difference between non–timeline-related losses of loans serviced by the Big 5 Servicers and those of loans serviced by smaller servicers post-NMS (the DID coefficient, 0.009). The hypothesis here is that even though post-NMS, the Big 5 Servicers had to incur higher non–timeline-related servicing costs than smaller servicers, they could not pass those additional costs to Freddie Mac because those costs are more overhead related.

We also use the GSE foreclosure moratoria to conduct a placebo test. The idea is that GSE foreclosure moratoria applied to all loans, no matter whether they are serviced by the Big 5 Servicers or smaller servicers and no matter whether they are owner-occupied property loans or investment loans. Therefore, we should not expect a treatment (DID) effect. Results in Appendix Table 3 confirm that this is exactly what we see in the data.

In summary, the DID tests suggest causal impacts on loss severities from the changes in the servicing industry resulting from the NMS and CFPB servicing rules, coming from the extension of foreclosure timelines and increases in non–timeline-related costs. Note that the DID results presented in the aforementioned tables should be treated as lower bound estimates of the impact

[39] Costs can be passed on to servicers through secondary market sales of mortgage servicing rights (MSRs); recent sales activity indicates this is the case (see *Inside Mortgage Finance* 2016). But these do not directly impact servicing expenses captured here.

of those events because there could be spillover effects between the treatment group and the control group, and certain servicers could have adopted the rules in anticipation of their taking effect. Thus, the tests are biased *against* finding significant differences because effects caused by the freezing of foreclosures between September 2010 and October 2012 that impacted our control group also raised timelines and severity rates for them.

3.3 Summing Up: Estimating the economic impacts of the new servicing rules

Although statistical significance in our DID tests is evidence of causality, it does not measure the economic impact of these new servicing rules. As a final analysis, we put the policy changes and events into a loss severity regression to directly measure their incremental impacts on loss severity rates, comparing them with pre-crisis timelines and severity rates. What we do differently in Table 7 from Table 3 is that, instead of using time dummies for liquidation timing, we use dummy variables for loans that were affected by the three major events, namely, the robo-signing scandal, the NMS, and the CFPB servicing rules. In Table 7, loans affected by the robo-signing scandal are those loans serviced by the Big 5 Servicers that fell into delinquency or were foreclosed between September 2010 and October 2012. Loans affected by the NMS are owner-occupied property loans serviced only by the Big 5 Servicers that fell into delinquency or were foreclosed between October 2012 and January 2014. Finally, loans affected by the CFPB servicing rules are owner-occupied properties that were foreclosed after January 2014. This last group is our focus because the CFPB servicing rules *is* the current regime that started in 2014. In so doing, we are using both the time series and cross-sectional variations to help with identification in our regression.

Results in Table 7 suggest that non–timeline-related loss severity rates increased by 2%, 3% and 7% after the robo-signing scandal, NMS and CFPB, respectively. All these changes are statistically significant. Recall that these effects are in addition to the impact of prolonged liquidation timelines and delayed liquidation timing already captured by other variables in the model. Using these results in Table 7, we can provide some rough estimates to measure the combined impact of prolonged liquidation timelines and growth in non–timeline-related losses in the current market affected by the CFPB servicing rules, comparing them to severity rates pre-crisis.

To test the robustness of our model, we compare out-of-sample performance of models with and without considering regime shifts. Table 8 shows our results. Here we use liquidations before 2011 to estimate the models and then predict loss severity rates of loans liquidated after 2011. The model without considering regime shifts significantly under-predicts loss severity rates in recent years, by 3%, 16%, and 23% in 2013, 2014, and 2015, respectively. By contrast, the model that incorporates regime shifts works well in out-of-sample prediction.

To get a rough estimate of severities in the new regime, we start by using our foreclosure timeline model to project timelines for loans that fell into serious delinquency after January 2014 and have either been liquidated or are still in serious delinquency. For these loans, the average liquidation timelines are estimated to be 31 months in nonjudicial states and 38 months in judicial states. These can then be compared against pre-crisis (2000–2006) average liquidation timelines of 12 and 15 months in nonjudicial and judicial states. We estimate that increases in loss severity rates resulting from these timeline increases will be 11 percentage points in nonjudicial states and 14 percentage points in judicial states.[40] To these we add the additional seven percentage points of non–timeline-related losses due to the CFPB rules from Table 7.

Summing up, we estimate that the marginal impact of the new regime will be an increase in loss severities from pre-crisis levels by roughly 18 percentage points in nonjudicial states and 21 percentage points in judicial states.[41] Given that the pre-crisis average loss severity rates for nonjudicial and judicial states are 9% and 16% (2000–2006 average), respectively, we expect average loss severity rates to be around 27% in nonjudicial states and 37% in judicial states going forward. These compare with 39% for nonjudicial states and 43% for judicial states during the 2007 to 2013 crisis period. Even with these improvements, severity rates are expected to be two to three times what they were pre-crisis. Increases in loss rates of this size are bound to have repercussions for pricing and, potentially, mortgage credit availability.

4. Conclusions and Discussion

Despite its importance, research work on mortgage LGD, or loss severities, is sparse, mainly because of data limitations. Thus, the release of GSE loan-level loss data provides a unique opportunity to study residential mortgage severities, especially so because the GSE data contain

[40] This is obtained by, e.g., multiplying 18 additional months (30 – 12 months) by the coefficient on the liquidation timeline for nonjudicial states ($18 \times 0.6\% \approx 11\%$) for nonjudicial states.

[41] A more precise calculation will require projection of several variables in our models, such as the mark-to-market LTV at liquidation, liquidation type, local SDQ rate, and some other variables.

detailed information on the components of loss severity encompassing the full boom, bust, and recovery periods during a period of profound change in the U.S. mortgage market. Our analysis generates a number of important findings that have important implications for our understanding of the financial crisis and the future of the housing finance system in the U.S.

First, the rise of loss severities from the early 2000s to the crisis period is substantial. Loss severity rates of Freddie Mac FRM loans more than tripled; we expect increases in severities on their nontraditional mortgages not included in this sample were even higher. Although research on the downfall of the GSEs has focused on the sharp rise in mortgage defaults, no study has systematically studied the contribution of loss severities tied to these defaults. A tripling of loss severities on their traditional business clearly played a role, so it will be important to make this a part of future research on the insolvency of the GSEs during the financial crisis.

Second, although our results are not fully time tested, we support the work of recent policy analysts that the persistently high loss severities post-crisis reflects a regime shift that could have a profound impact not only on mortgage servicing but also on the availability of credit for higher-risk borrowers. In this paper, we show how the new servicing standards stemming from the NMS and CFPB servicing rules have contributed to this regime shift. On the one hand, under the new regime, liquidation expenses are higher because of persistently longer foreclosure timelines, consistent with results reported for the broader mortgage market in Cordell et al. (2015). Compounding this, time-invariant liquidation expenses have also risen significantly. This combination of factors has resulted in record-high loss severities during a period when the mortgage market has recovered from the crisis. This regime shift has certainly greatly increased the cost of servicing delinquent mortgages, so much so that some large servicers are exiting large parts of the business altogether.[42] More importantly, policy analysts now claim it is affecting the provisioning of mortgage credit on the origination side, giving rise to the "squeaky clean" loan with minimal risk of even going delinquent, potentially disadvantaging low- to moderate-income

[42] In his 2015 *Annual Report to Shareholders*, JPMorgan CEO Jamie Dimon explained why it sold off its GNMA business and were negotiating arrangements to have the GSEs service their own delinquent loans: "We do not want to be in the business of foreclosure because it is exceedingly painful for our customers, and it is difficult, costly and painful to us and our reputation" (p. 36).

borrowers with limited or weaker credit.[43] This is certainly not something the CFPB intended, so more work in this area is urgently needed.

Although our analysis focuses on costs, we need to point out that the new CFPB rules do indicate that they are improving outcomes for borrowers by providing more opportunities for loan modifications, allowing more borrowers to stay in their homes (see Cordell and Lambie-Hanson, 2016). More cost–benefit analysis is needed on this score by linking these benefits to the potential costs of tighter credit.

We also find mortgage insurance recoveries play an important role in mitigating Freddie Mac's mortgage losses. We show how haircuts MIs make to lost interest and allowable expenses have grown, further increasing loss severities to investors. These increased costs need to be factored into loss estimations.

On a practical level, all of these factors will play into the pricing of credit risk for the GSEs' fast-growing CRT business. To that end, models developed in this paper can help the investment community more accurately estimate losses. Our models can also be used in stress testing and other applications.

On an academic level, our findings show that losses can be underestimated by not considering the regime shift taking place in the U.S. mortgage market. From this perspective, our results support the notion that statistical models can fail if they do not incorporate specific institutional settings and structural breaks in models, as argued by Rajan, Seru, and Vig (2015).

It is worth mentioning that we only focus on 30-year FRMs in this paper. It would be interesting to extend this analysis to draw comparisons with the private-label market, where loan-level loss data also exist. We leave these topics for future research.

[43] See Laurie Goodman, "Servicing Costs and the Rise of the Squeaky-Clean Loan," Mortgage Banking, February 2016.

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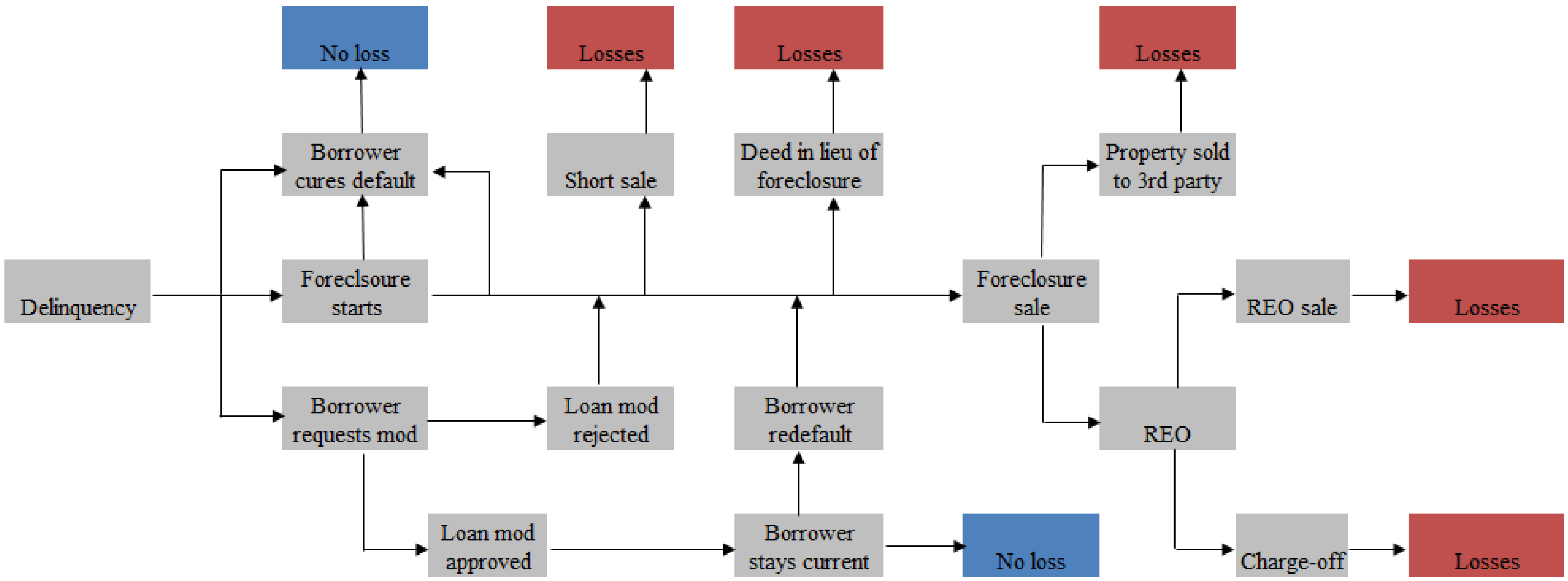


Figure 1 Typical Default Process

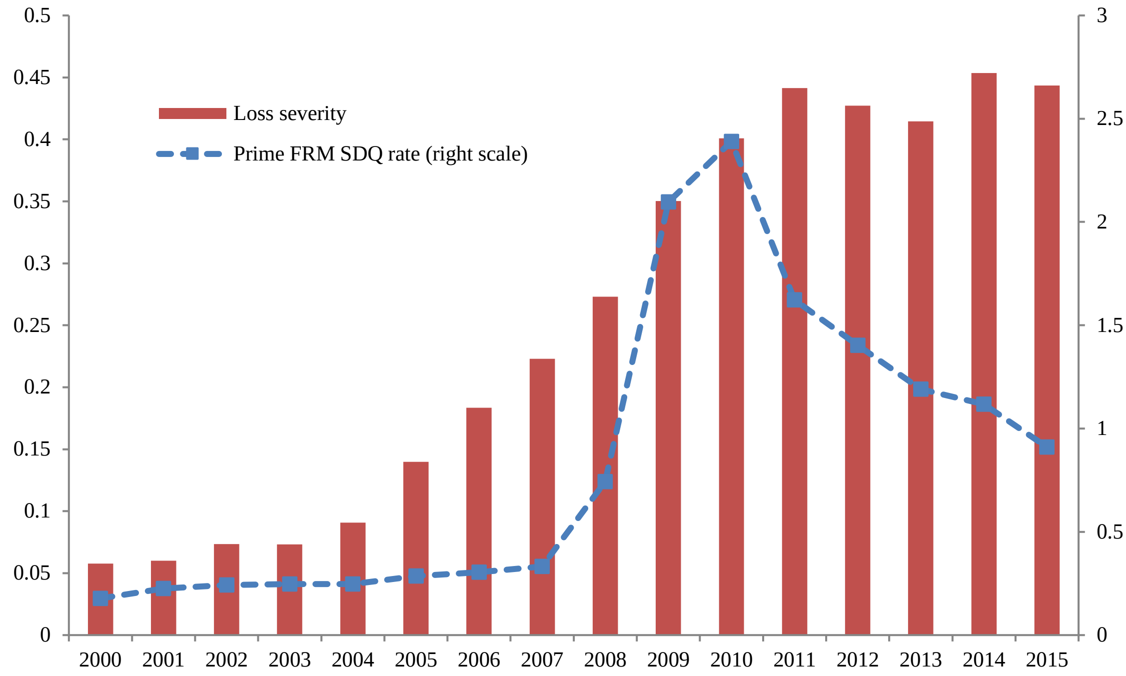


Figure 2 Loss Severities of Freddie Mac Loans by Year of Liquidation

Notes: The bars depict weighted average loss severity rates of loans liquidated in the calendar year (left scale); the dashed line represents SDQ rates of prime fixed-rate mortgage loans (right scale). Loss severity numbers are calculated based on the Freddie Mac data, and the SDQ data are from Mortgage Banks Association's National Delinquency Survey. Freddie Mac loans included here are first-lien, full-documentation, and fully amortizing 30-year fixed-rate mortgages for single-family homes that were liquidated; these loans were originated between 1999 and 2013 and liquidated between 2000 and 2015. Loss severity is defined as (net sales proceeds + MI recoveries + non-MI recoveries – UPB – carrying costs – expenses) ÷ UPB. Expenses include all allowable expenses that Freddie Mac bears in the process of acquiring, maintaining, and/or disposing of properties. Carrying costs is calculated as described in Section 2. Non-MI recoveries include proceeds from repurchase or make-whole proceeds, tax and insurance refunds, hazard insurance proceeds, rental receipts, and positive escrow.

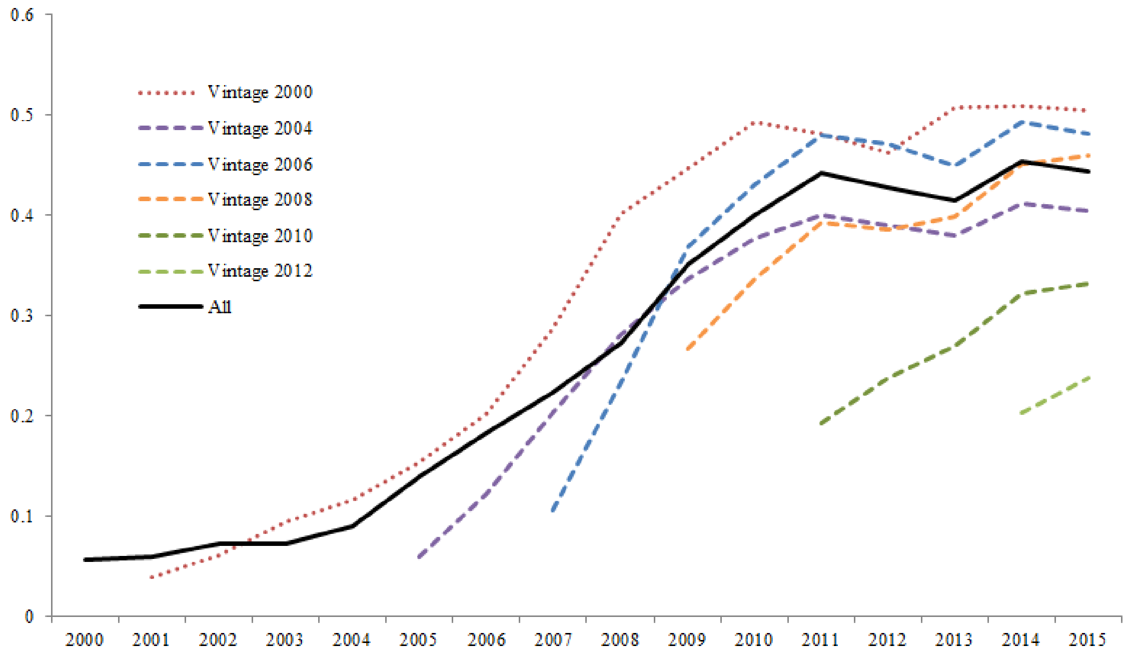


Figure 3 Freddie Mac Loan Loss Severities by Year of Liquidation: Combined and by Vintage

Notes: The solid black line shows the numbers for all vintages combined and the colored dashed lines are for each vintage. These numbers are weighted averages calculated with UPB used as the weight. Other vintages (1999, 2001, 2002, 2003, 2005, 2007, 2009, 2010, 2011, 2012, and 2013) are not shown in this chart for visual reasons but are included in the combined sample calculations.

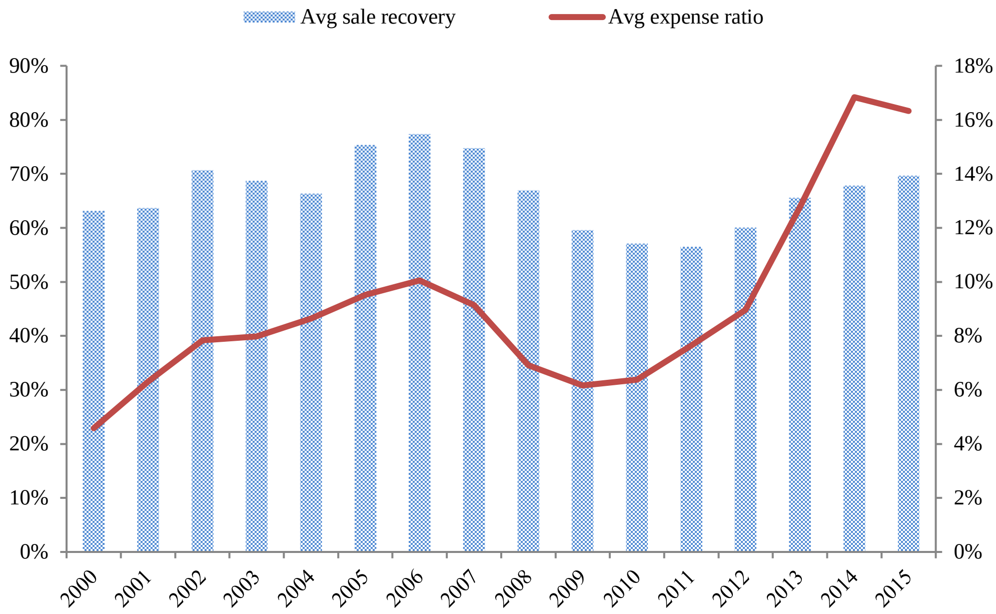


Figure 4 Average Sales Recovery Ratio and Expense Ratio

Notes: The bars show the average sales recovery as a percentage of default UPB, and the line shows the average expenses as a percentage of default UPB. Sales recoveries are net of sales costs (commissions). These number are weighted averages based on our Freddie Mac loan-level loss data, with UPB used as the weight.

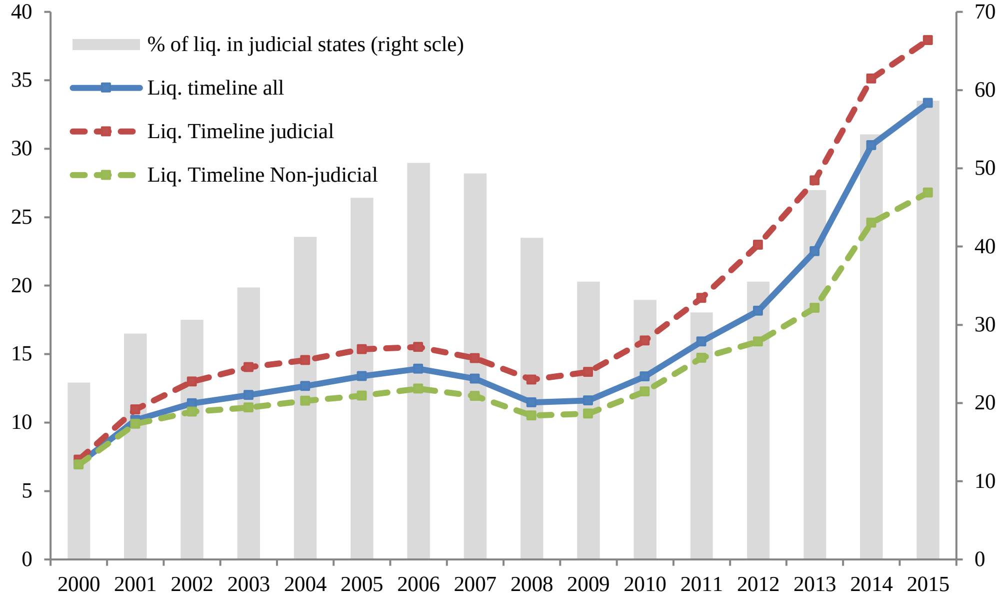


Figure 5 Average Liquidation Timeline by Year of Liquidation

Notes: The lines show the average liquidation timeline, and the bars show the share of liquidated loans in judicial states. Liquidation timeline is calculated as the number of months from SDQ to final liquidation, either in the form of REO sales or foreclosure alternatives such as short sales, note sales, and charge offs.

Table 1 Loss Severity and its Components of Freddie Mac Loans

Variable	Mean	Std Dev	P1	Q1	Median	Q3	P99
Loss severity	0.424	0.317	-0.125	0.173	0.412	0.642	1.215
Net sale proceeds	0.596	0.287	0.000	0.398	0.603	0.800	1.255
Liquidations expenses	0.118	0.097	0.001	0.048	0.095	0.162	0.479
Carrying costs	0.044	0.024	0.009	0.028	0.037	0.052	0.498
MI recoveries	0.081	0.130	0.000	0.000	0.000	0.178	0.397
for loans with MI	*0.215*	*0.128*	*0.000*	*0.128*	*0.267*	*0.317*	*0.397*
Non-MI recoveries	0.034	0.086	0.000	0.003	0.009	0.019	0.379
Number of loans				339,217			

Notes: Data are from Freddie Mac. Loans included here are first-lien, full-documentation, and fully amortizing 30-year fixed-rate mortgages for single-family homes that were liquidated. These loans were originated between 1999 and 2013 and liquidated between 2000 and 2015. Bad data and outliers (e.g., those with extremely high loss severity and those with missing LTV information) are excluded. Loss severity is defined as (net sales proceeds + MI recoveries + non-MI recoveries – UPB – carrying costs – expenses) ÷ UPB. Expenses include all allowable expenses that Freddie Mac bears in the process of acquiring, maintaining, and/or disposing of properties, even though property selling expenses such as commission is taken into consideration separately (in net sales proceeds). Carrying costs are calculated in two parts: the first part is the lost interest expense for the first 120 days plus Freddie Mac's cost of funds the remaining months until the loan is liquidated. Non-MI recoveries include proceeds from repurchase/make whole proceeds, tax and insurance refunds, hazard insurance proceeds, rental receipts, and positive escrow.

Table 2 Summary Statistics

Variable	Mean	Std Dev	P1	Median	P99
Original loan amount	161,565	86,490	40,000	142,000	399,000
Default UPB	153,899	83,588	37,415	135,158	384,097
Contemporaneous (mark-to-market) LTV	99.55	26.39	53.47	95.89	177.36
Origination LTV	81.37	10.14	53	80	100
Borrower FICO score	687	55	568	684	802
Home purchase loan	0.34	0.47	0	0	1
Cash-out refinance loan	0.38	0.49	0	0	1
Rate/term refinance loan	0.28	0.45	0	0	1
Owner-occupied property loan	0.89	0.31	0	1	1
Second/vacation home loan	0.03	0.17	0	0	1
Investment properties	0.08	0.28	0	0	1
Loan size (log origination balance)	11.85	0.56	10.60	11.86	12.90
REO liquidation (vs. other foreclosure alternatives)	0.69	0.46	0	1	1
Liquidation timeline (months)	18.18	12.37	1	15	62
Loan with mortgage insurance (MI)	0.37	0.48	0	0	1
MI coverage percentage for MI loans	25.5	6.5	12	25	35
Current quarter zip code SDQ rate	0.03	0.02	0.01	0.03	0.10
State-level foreclosure pipeline volume	0.07	0.02	0.02	0.08	0.10
Loan in judicial state	0.41	0.49	0	0	1
Loan in redemption state	0.17	0.38	0	0	1
Loan serviced by a large servicer	0.60	0.49	0	1	1
Loan serviced by a small servicer	0.21	0.41	0	0	1
Number of loans			339,217		

Notes: Contemporaneous LTV is calculated based on origination LTV and HPI, which is at the three-digit zip code–level that we construct based on the CoreLogic five-digit zip code–level HPI; zip code SDQ rate is calculated based on the McDash Analytics data; state-level foreclosure pipeline volume is the number of loans that are more than 60 days delinquent or in foreclosure normalized by the total number of loans outstanding calculated based on the McDash Analytics data; large servicers are defined as the top five servicers in the Freddie Mac sample, and small servicers are those with less than 1% of market share in the Freddie Mac sample.

Table 3 GLS Estimates of the Loss Severity Regression

	Full Sample		Loans without MI	
	Model 1	Model 2	Model 1	Model 2
Contemporaneous LTV spline function				
<=100%	0.5148***	0.5253***	0.6166***	0.6232***
	(0.0215)	(0.0206)	(0.0333)	(0.0337)
>100%	0.5029***	0.5083***	0.5954***	0.5991***
	(0.0174)	(0.0168)	(0.0260)	(0.0267)
Zip code–level SDQ rate	1.6627**	1.6345***	1.3190**	1.3214**
	(0.6390)	(0.6003)	(0.5714)	(0.5374)
State-level foreclosure pipeline volume	1.2920***	1.6012***	1.1849***	1.5880***
	(0.2970)	(0.2738)	(0.3117)	(0.2742)
Liquidation timeline spline function				
<=6 months		0.0061***		0.0053***
		(0.0009)		(0.0011)
6–36 months		0.0067***		0.0063***
		(0.0004)		(0.0004)
>36 months		0.0059***		0.0055***
		(0.0003)		(0.0003)
Liquidated during 2009–2012	0.0503***	0.0043	0.0510***	0.0008
	(0.0158)	(0.0118)	(0.0184)	(0.0132)
Liquidated during 2012–2014	0.1173***	0.0381***	0.1087***	0.0283**
	(0.0141)	(0.0099)	(0.0163)	(0.0114)
Liquidated after 2014	0.2205***	0.1191***	0.2086***	0.1080***
	(0.0136)	(0.0117)	(0.0148)	(0.0135)
Loan seasoning	Y	Y	Y	Y
Loan characteristics	Y	Y	Y	Y
Borrower FICO	Y	Y	Y	Y
Liquidation type (REO vs. non-REO)	Y	Y	Y	Y
Loan vintage-fixed effect	Y	Y	Y	Y
State × servicer-fixed effects	Y	Y	Y	Y
Number of observations	302,163	302,163	195,329	195,329
Adjusted R-squared	0.536	0.559	0.511	0.533

Notes: The dependent variable is the loss severity rate; the reciprocal of default UPB is used as the weight in the regression; corrected standard errors are in parentheses assuming error-term clustering at the state level; *** for p<0.01%, ** for p<0.1%, and * for p<5%. See Appendix Table 1 for the full model estimates. The following filters are applied to the loan sample so the sample size is slightly smaller than that of Table 2: repurchased loans are excluded; origination LTV has to be between 47 and 100 percent; contemporaneous (mark-to-market) LTV needs to be populated; and, finally, foreclosure timeline outliers and loan age outliers are excluded.

Table 4 MLE Estimates of the Accelerated Failure Time Model for Liquidation Timelines

		Judicial	Nonjudicial
Default timing			
	After Jan. 2014	1.147***	1.580***
		(0.011)	(0.011)
	Oct. 2012–Jan. 2014	1.073***	1.484***
		(0.009)	(0.01)
	Sept. 2010–Oct. 2012	1.024***	1.312***
		(0.008)	(0.009)
	Nov. 2008–Aug. 2010	0.809***	1.207***
		(0.009)	(0.01)
	Feb. 2007–Oct. 2008	0.594***	1.059***
		(0.009)	(0.011)
CLTV		Y	Y
State-level foreclosure pipeline volume		Y	Y
Previous 12-month HPA		Y	Y
Deficiency judgment		Y	Y
Redemption state		Y	Y
Loan characteristics		Y	Y
Borrower FICO		Y	Y
Intercept		Y	Y
Scale		Y	Y
Number of observations		225,244	285,291
-2LogL		439,341	676,186

Notes: 1) these are MLE estimates of the accelerated failure time model. See Cordell et al. (2015) for a detailed discussion of the model; standard errors are in parenthesis; *** for p<0.01%, ** for p<0.1%, and * for p<5%. See Appendix Table 2 for the full model estimates.

Table 5 Liquidation Timelines Difference-in-Differences Tests

Panel A: Owner-occupied property loans as treatment group

	NMS	CFPB Servicing Rules
Owner	-0.008	-0.028
	(0.014)	(0.016)
Post-event	0.278***	0.336***
	(0.030)	(0.030)
Owner × Post-event	0.264***	0.231***
	(0.030)	(0.030)
Control variables	Y	Y
State × servicer FE	Y	Y
Observations	37,423	55,928
-2LogL	72,744	61,320

Panel B: Loans serviced by the Big 5 Servicers as treatment group

	NMS	CFPB Servicing Rule
Big 5 Servicer	-0.379***	0.143***
	(0.010)	(0.011)
Post-event	0.041**	0.625***
	(0.014)	(0.015)
Big 5 servicer × Post-event	0.136***	-0.118***
	(0.020)	(0.018)
Control variables	Y	Y
State × servicer FE	Y	Y
Observations	87,130	51,485
-2LogL	185,136	54,609

Notes: These panels present the difference-in-differences (DID) tests of the impact of changes in the servicing industry on foreclosure timelines. The DID test is in the form of $Y = \beta_1 T + \beta_2 T * A + \beta_3 A + Z'\gamma$, where T represents the treatment group, A represents the period after an event, and the Z vector represents a vector of control variables. The model estimated is an accelerated failure time model as in Table 4. In panel A, we limit loans to be those serviced by the Big 5 Servicers in judicial states; the treatment group here are owner-occupied property loans, which are the target of both the NMS and the CFPB servicing rules, and the control group are investor property loans, which are not the target of either NMS or CFPB. In panel B, we limit loans to be owner-occupied property loans in judicial states; the treatment group are loans serviced by the Big 5 Servicers, which are the target of the NMS. In both panels, the events are NMS in column 1 and CFPB in column 2, respectively. ***, **, and * indicate 0.1%, 1%, and 5% significance, respectively.

Table 6 Loss Severity Rates Difference-in-Differences Tests

Panel A: Owner-occupied property loans as treatment group

	NMS	CFPB Servicing Rules
Owner	-0.128***	-0.093***
	(0.008)	(0.008)
Post-event	0.057***	0.078***
	(0.013)	(0.020)
Owner × Post-event	0.034***	0.014*
	(0.012)	(0.008)
Control variables	Y	Y
State × servicer FE	Y	Y
Observations	12,923	11,273
Adjusted R-squared	0.523	0.518

Panel B: Loans serviced by the Big 5 Servicers as treatment group

	NMS	CFPB Servicing Rule
Big 5 Servicers	0.030***	0.017***
	(0.005)	(0.005)
Post-event	0.084***	0.102***
	(0.007)	(0.014)
Big 5 Servicers × Post-event	0.009	-0.028**
	(0.008)	(0.013)
Control variables	Y	Y
State × servicer FE	Y	Y
Observations	13,914	21,095
Adjusted R-squared	0.478	0.532

Notes: These panels present the DID tests of the impact of changes in the servicing industry on loss severity rates. The DID test is in the form of equation 3. In panel A, we limit loans to be those serviced by the Big 5 Servicers in judicial states; the treatment group is are owner-occupied loans, which are the target of both the NMS and the CFPB servicing rules; the control group is investor property loans, which are not the target of either NMS or CFPB. In panel B, we limit loans to be owner-occupied property loans in judicial states; the treatment group are loans serviced by the Big 5 Servicers, which are the target of the NMS. In both panels, the events are NMS in column 1 and CFPB in column 2, respectively. ***, **, and * indicate 0.1%, 1%, and 5% significance, respectively.

Table 7 Impact of Servicing Policy Change: Estimates from Loss Severity Rate Regression

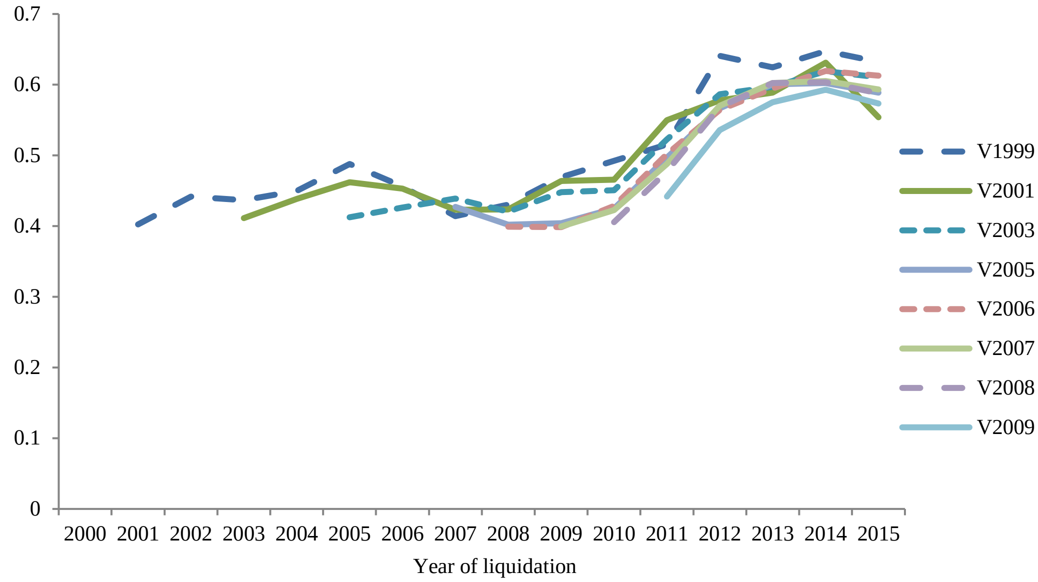
	Full Sample	Loans without MI
Loans affected by the robo-signing scandal	0.019***	0.010***
	(0.001)	(0.001)
Loans affected by the NMS	0.027***	0.022***
	(0.002)	(0.002)
Loans affected by the CFPB servicing rules	0.072***	0.067***
	(0.002)	(0.002)
Contemporaneous LTV	Y	Y
Zip code–level SDQ rate	Y	Y
State-level foreclosure pipeline volume	Y	Y
Liquidation timeline spline function	Y	Y
Loan seasoning	Y	Y
Loan characteristics	Y	Y
Borrower FICO	Y	Y
Liquidation type (REO vs. non-REO)	Y	Y
Loan vintage-fixed effect	Y	Y
State × servicer-fixed effects	Y	Y
Number of observations	302,163	195,328
Adjusted R-squared	0.556	0.532

Notes: The dependent variable is the loss severity rate; the reciprocal of default UPB is used as the weight in the regression; corrected standard errors are in parentheses assuming error-term clustering at the state level; *** for p<0.01%, ** for p<0.1%, and * for p<5%. Loans affected by the robo-signing scandal satisfy the following criteria: the loan fell into delinquency between September 2010 and April 2012 or a foreclosure or foreclosure alternative completed between September 2010 and April 2012; the loan was serviced by the Big 5 Servicers. Loans affected by the NMS are those that fell into delinquency between October 2012 and January 2014 or liquidated via foreclosure or foreclosure alternative between October 2012 and January 2014, were owner-occupied loans, and were serviced by servicers covered by NMS. Loans affected by the CFPB servicing rules are those that were liquidated via foreclosure or foreclosure alternative after January 2014 and were owner-occupied property loans. The full model results are not shown here because of space limitations, but they are available on request.

Table 8 Out-of-Sample Prediction Error

	Without Incorporating Regime Shift		Incorporating Regime Shift	
	Prediction Error	% Prediction Error	Prediction Error	% Prediction Error
2012	0.004	1%	0.016	3%
2013	-0.016	-3%	0.002	0%
2014	-0.081	-16%	-0.027	-5%
2015	-0.109	-23%	-0.026	-6%

Notes: We use loans liquidated before 2011 to estimate the model and then predict loss severity rates of loans liquidated after 2011. Prediction error is calculated as predicted value minus actual value, therefore, a negative prediction error indicates under-prediction by the model (with and without regime shift factors; see Table 7 for the one with regime shift factors). We limit loans to be those originated before 2010 without mortgage insurance.



Appendix Figure 1 Mortgage Insurance (MI) Claim Haircuts

Notes: MI claim haircut is calculated as (MI recoveries − UPB × MI coverage percentage) ÷ ([accrued interest + liquidation expenses] × MI coverage percentage). Medians are shown on the chart. The overall average haircut is about 50 percent.

Appendix Table 1 Full Loss Severity Model Estimates

		Full Sample	Loans without MI
Contemporaneous LTV spline function			
	<=100%	0.5253***	0.6232***
		(0.0206)	(0.0337)
	>100%	0.5083***	0.5991***
		(0.0168)	(0.0267)
Zip code–level SDQ rate		1.6345***	1.3214**
		(0.6003)	(0.5374)
State-level foreclosure pipeline volume		1.6012***	1.5880***
		(0.2738)	(0.2742)
Liquidation timeline spline function			
	<=6 months	0.0061***	0.0053***
		(0.0009)	(0.0011)
	6–36 months	0.0067***	0.0063***
		(0.0004)	(0.0004)
	>36 months	0.0059***	0.0055***
		(0.0003)	(0.0003)
Liquidated during 2009–2012		0.0043	0.0008
		(0.0118)	(0.0132)
Liquidated during 2012–2014		0.0381***	0.0283**
		(0.0099)	(0.0114)
Liquidated after 2014		0.1191***	0.1080***
		(0.0117)	(0.0135)
Loan age less than 3 years at delinquency		-0.0222***	-0.0210***
		(0.0033)	(0.0041)
Original LTV <65%		-0.0525***	-0.0351***
		(0.0049)	(0.0050)
Original LTV 80%–90%		0.0087***	-0.0650***
		(0.0030)	(0.0173)
Original LTV >90%		-0.0084	-0.0274
		(0.0066)	(0.0188)
Loan size spline function			
	<=200k	-0.0282***	-0.0283***
		(0.0024)	(0.0028)
	200–400k	-0.0192***	-0.0192***
		(0.0014)	(0.0016)
	>400k	-0.0132***	-0.0132***
		(0.0008)	(0.0009)
Cash-out refinance		0.1041***	0.1075***
		(0.0050)	(0.0068)
Term/rate refinance		0.0791***	0.0822***
		(0.0053)	(0.0073)
Second home		0.0364***	0.0425***

	(0.0077)	(0.0067)
Investment property	0.1265***	0.1276***
	(0.0079)	(0.0085)
Borrower FICO <620	0.0197***	0.0229***
	(0.0033)	(0.0042)
Borrower FICO 680–720	-0.0119***	-0.0143***
	(0.0017)	(0.0022)
Borrower FICO >720	-0.0234***	-0.0270***
	(0.0035)	(0.0045)
MI coverage percentage	-0.7831***	
	(0.0211)	
REO liquidation	0.0663***	0.0877***
	(0.0053)	(0.0076)
Loan vintage-fixed effect	Y	Y
State × servicer-fixed effects	Y	Y
Number of observations	302,163	195,329
Adjusted R-squared	0.559	0.533

Notes: The dependent variable is the loss severity rate; the reciprocal of default UPB is used as the weight in the regression; corrected standard errors are in parentheses assuming error-term clustering at the state level; *** for p<0.01%, ** for p<0.1%, and * for p<5%. The reference groups for the categorical variables are LTVs between 65% and 80%; home purchase loans; owner-occupied properties; FICO scores between 620 to 680; and foreclosure alternatives, respectively. See Table 2 for variable definitions.

Appendix Table 2 Full Timeline Model Estimates

	Judicial States	Non-judicial States
Default timing bucket		
After Jan. 2014	1.147***	1.58***
	(0.011)	(0.011)
Oct. 2012–Jan. 2014	1.073***	1.484***
	(0.009)	(0.01)
Sept. 2010–Oct. 2012	1.024***	1.312***
	(0.008)	(0.009)
Nov. 2008–Aug. 2010	0.809***	1.207***
	(0.009)	(0.01)
Feb. 2007–Oct. 2008	0.594***	1.059***
	(0.009)	(0.011)
Contemporaneous LTV bucket		
<=80%	0.48***	0.471***
	(0.009)	(0.008)
80%–100%	0.308***	0.312***
	(0.008)	(0.007)
100%–120%	0.207***	0.19***
	(0.009)	(0.007)
State-level foreclosure pipeline volume	2.998***	3.557***
	(0.064)	(0.105)
Previous 12-month HPA bucket		
<=-10%	-0.718***	-1.207***
	(0.013)	(0.01)
-10%–0%	-0.446***	-0.947***
	(0.006)	(0.006)
0%–5%	0.007	-0.133***
	(0.006)	(0.005)
Deficiency judgment allowed	0.22***	-0.052***
	(0.059)	(0.005)
Redemption state	0.192***	-0.27***
	(0.008)	(0.005)
Loan size bucket	-0.576***	-0.528***
<= 100k	(0.025)	(0.02)
	-0.383***	-0.311***
100–200k	(0.025)	(0.019)
	-0.159***	-0.134***
200–400k	(0.025)	(0.019)
Cash-out refinance	0.037***	0.111***
	(0.005)	(0.005)
Rate/term refinance	-0.04***	0.045***
	(0.005)	(0.005)

Owner occupied	0.163***	0.229***
	(0.008)	(0.008)
Second home	-0.005	0.041**
	(0.015)	(0.015)
Borrower FICO score bucket		
<=680	0.214***	0.264***
	(0.005)	(0.005)
680–720	0.121***	0.134***
	(0.006)	(0.006)
Intercept	1.76***	1.333***
	(0.065)	(0.024)
Scale	0.847***	1.004***
	(0.002)	(0.002)
Number of observations	225,244	285,291
-2LogL	439,341	676,186

Notes: These are accelerated failure time model estimates. See, Cordell et al. (2015) for a detailed discussion of the model; standard errors are in parenthesis; *** for p<0.01%, ** for p<0.1%, and * for p<5%. The reference groups for the categorical variables are default before February 2007, contemporaneous LTV greater than 120%, previous 12-month house price appreciation greater than 5%, non-deficiency judgment state, non-redemption state, loan size greater than 400k, home purchase loans, investment properties, and FICO score greater than 720, respectively.

Appendix Table 3 Placebo Tests

Panel A: Owner-occupied property loans as treatment group

	Foreclosure Moratoria
Owner	0.045
	(0.024)
Post-event	0.660***
	(0.025)
Owner × Post-event	-0.023
	(0.026)
Control variables	Y
State × servicer FE	Y
Observations	25,200
-2LogL	32,831

Panel B: Loans serviced by the Big 5 Servicers as treatment group

	Foreclosure Moratoria
Big 5 Servicer	0.054***
	(0.011)
Post-event	0.664***
	(0.010)
Big 5 Servicer × Post-event	-0.019
	(0.012)
Control variables	Y
State × servicer FE	Y
Observations	34,747
-2LogL	47,419

Notes: these panels present results of placebo tests in a DID framework. The DID test is in the form of equation 3. The model estimated is an accelerated failure time model as in Table 4. In panel A, we limit loans to be those serviced by the big five services in judicial states; the treatment group is owner-occupied properties and the control group is investor properties. In panel B, we limit loans to be those owner-occupied property loans in judicial states; the treatment group is loans serviced by the big five services. In both panels, the event is GSE foreclosure moratoria starting in November 2008. Because the moratoria apply to all loans, we would not expect a significant treatment group effect. ***, **, and * indicate 0.1%, 1%, and 5% significance, respectively.