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Mortgage Foreclosure Risk After the Great Recession

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ABSTRACT

The objective of increased regulation of mortgage origination activities after the Great Recession was to prevent another foreclosure crisis in the future. However, the literature is not conclusive about the actual effect of these policy changes. By using the 2007-09 panel and subsequent waves of the Survey of Consumer Finances (SCF), we predict foreclosure risk based on individual borrower characteristics. We show that the median mortgage foreclosure probability kept decreasing after 2010, but in 2016 it was still higher relative to the year 2007. The median foreclosure probability has remained high among both non-bank borrowers and bank borrowers. The regulatory changes started in 2010, so we also compare predicted foreclosure probabilities to the levels in 2010 and find that, despite the fact that banks were affected by this regulation more than non-banks, predicted foreclosure probabilities for bank mortgages declined slower than for non-bank mortgages. Our findings offer support for a thorough analysis of the regulatory effects because they might have been weaker than expected or worked in an unexpected way.

Keywords: Residential mortgages Foreclosure Non-banks Lending.

JEL codes: C53, G21, G23.

1 Introduction

A rise in mortgage delinquencies in the US in 2007 paved the path to the global financial crisis and further escalated into the foreclosure crisis.[1] To avoid another foreclosure crisis in the future new regulatory measures for mortgage origination and servicing were introduced. However, the impact of these regulations were asymmetric for banks and non-banks: Banks faced tighter regulations and reduced mortgage origination.[2] Consequently, non-bank's share in mortgage origination increased from 20% in 2007 to 50% in 2016 (Buchak et al., 2018; Kim et al., 2018). Given the rise of non-banks, it remains unclear whether the aggregate foreclosure risk in the US has declined.

This paper documents how the distribution of foreclosure probabilities in the US has evolved since the crisis and the contribution of banks and non-banks to it. We find that foreclosure risk predicted based on individual borrower characteristics has developed in a highly non-linear form since 2007: it reached a peak in 2010 and kept declining since. However, in 2016 the median foreclosure probability was still 27% higher than in 2007. In other words, given the current characteristics of mortgage borrowers, the residential mortgage market in the US was not more resilient to a fall in housing prices in 2016 than it was in 2007.

Given the increased non-bank role in the mortgage market, we also investigate whether higher median foreclosure probability is associated with the less regulated financial institutions only – non-banks. We find that the non-bank sector contributed to high foreclosure risk in 2016 to a large extent: mortgages associated with non-banks had substantially riskier characteristics.[3] However, the increase in aggregate foreclosure risk is only partially driven by the non-banks' sector, because relative to the year 2007, predicted foreclosure probabilities remained elevated in both bank and non-bank sectors. More specifically, we find that, regardless of lender type, borrower characteristics predict higher foreclosure rate in 2016 compared to 2007 in case housing prices fall again.

Although the rise of non-banks motivates our research question, this analysis cannot distinguish the role of aggregate shocks from regulatory effects on foreclosure risk. The main regulatory reforms started in 2010 and coincided with the peak of the foreclosure crisis, so the decline in foreclosure risk after 2010 can be potentially attributed to both regulatory efforts and aggregate shocks. However, regulatory changes mainly targeted banks and we acquire some insights by splitting the sample by lender type. We show that although the regulatory change mainly targeted banks, foreclosure risk declined in the non-bank segment of the market faster. This suggests that aggregate shocks might have played a larger role in the decline of aggregate foreclosure risk than the regulatory change. We conjecture that our finding raises the question of the effectiveness of regulation reforms and highlights the need of causal analysis of the regulation effects.

To achieve these results we first estimate the foreclosure probability model using the Survey of Consumer

[1] Lenders generally begin the foreclosure process once homeowners missed two or more mortgage payments. The length of the foreclosure process varies by states in US, depending on whether lenders can proceed without going to court, etc. The foreclosure sale happens after the lender obtains legal title to the property.

[2] Following Kim et al. (2018) and Buchak et al. (2018), in this paper non-banks refer to non-depository financial institutions. Therefore, all lenders with the exception of banks or credit unions are labeled as non-banks here.

[3] A large literature emphasizes that non-banks are more likely to be associated with mortgages which default or foreclose. See Alexander et al. (2002); Avery and Brevoort (2015); Ergungor and Moulton (2014); Ding et al. (2011) and Laderman et al. (2008) among others.

Finances (SCF) 2007-09 panel. The use of the SCF data is motivated by two reasons. First, the SCF extensively records household and mortgage characteristics. We use these characteristics as control variables in estimating and predicting foreclosure probabilities. Second, the survey weights and multiple imputation method in the SCF allows us to provide foreclosure probability estimates for the whole US population. By using the estimates from the foreclosure probability model and subsequent SCF waves we predict foreclosure probabilities in 2010, 2013 and 2016. This exercise allows us to test the resilience of the residential mortgage market in the US to the fall in housing prices as in 2009. Our results are based on analyzing the changes in the distribution of predicted foreclosure probabilities by lender type and over time.

The prediction model has two main limitations, which, we argue, are not key to our question. First, the model does not use aggregate variables. However, we do not aim at identifying the contribution of aggregate shocks to foreclosure but rather aim at capturing the combined effect of borrower characteristics and aggregate dynamics. Second, using the model estimated on data in 2007-09 to predict foreclosure in later years implicitly implies that banks used the same lending practices throughout the whole period. Arguably, banks lent more thoroughly in 2016 than in 2007, but more thorough applicant screening should be firstly reflected in borrower characteristics. We use an extensive set of variables to control for borrowers' liquidity, solvency and other factors that the literature finds important to explain differences in propensity to foreclose.

The literature uses different measures of mortgage distress. We choose to analyze foreclosure rather than mortgage delinquency for several reasons. Delinquent mortgages may still be repaid or restructured. In view of this, we look at a more precise measure of mortgage default. Also the SCF data does not provide information on delinquency duration, therefore, we cannot distinguish between mortgage borrowers who missed one payment and mortgage borrowers who are about to lose their house. The weakness of the foreclosure measure is that it may reflect not only borrower vulnerability but also lenders' reluctance to restructure delinquent mortgage debt. If a high level of securitization of non-bank mortgages reduces non-banks' incentives to renegotiate delinquent mortgages, we would observe higher rates of foreclosure among non-bank mortgages because of both renegotiation failure and riskier borrowers. However, the literature has not reached a consensus on this matter (e.g. Adelino et al. (2013) vs. Piskorski et al. (2010)) and as far as we know the transition rate from delinquency to foreclosure may not differ by lender type.

Related literature: Our paper is closely related to two strands of literature: difference between banks and non-banks with respect to mortgage foreclosure risk, and impact of regulation on banks and non-banks since the Great Recession. We discuss how our paper relates to the two strands separately.

Mortgage loans originated by non-banks are usually more likely to default or foreclose than loans originated by banks. Non-banks are associated with households who on average have lower income and lower credit scores (Buchak et al., 2018; Kim et al., 2018). Non-bank mortgage originations are also more likely to be inadmissible for GSEs guarantees, but guaranteed by FHA or VA (Buchak et al., 2018; Kim et al., 2018). However, the difference in default pattern persists, even after controlling for loan and other observable characteristics (e.g. Alexander et al. (2002); Avery and Brevoort (2015); Ergungor and Moulton (2014)). In this paper we provide summary statistics for bank and non-bank borrowers in the SCF dataset and confirm a higher financial vulnerability of non-bank borrowers. Our further findings control for observed borrowers characteristics and still find the difference in foreclosure patterns in line with the mentioned studies. The two common explanations for this persistence include differences in available information and applicant screening. Ergungor and Moulton (2014) suggest that banks with branch presence in a market may interact with the potential borrowers and the community more and may have an important informational advantage over non-local banks and non-bank financial institutions. The study establishes the advantages of soft information by showing that mortgages originated by banks perform better than non-bank mortgages, but mortgages originated by local banks that are closest to their clients perform the best. It concludes that if all banks are better positioned to use soft information in extending mortgages than non-banks, that partially explains why bank mortgages perform better. Applicant screening efforts depend on regulatory rules and inherent lenders' incentives. Banks differ from non-banks on both accounts. Differently from non-banks, banks are regulated by federal regulators such as bank regulators such as the Federal Deposit Insurance Corporation, the Federal Reserve Board, the Office of the Comptroller of the Currency, and the National Credit Union Association. The consensus is that bank regulatory requirements are stricter than non-bank regulatory standards. Although both the GSEs and Ginnie Mae set minimum requirements for their counterparties, the GSEs' regulator, the Federal Housing Finance Agency (FHFA), among other has called attention to lack of resources and formal access to examine third-parties and especially non-bank lenders (Kim et al., 2018). Ding et al. (2011); Laderman et al. (2008); Avery and Brevoort (2015) and many other studies establish that stricter regulatory environment for banks than non-banks thus encourages banks to screen borrowers better. For instance, banks originate fewer low documentation mortgages; Jiang et al. (2014) link low documentation mortgages with a higher probability of default. The exception is Keys et al. (2009) that finds that less capitalized banks may suffer from moral hazard problem more than non-banks .[4] Mortgage securitization reduces lenders' incentives to screen applicants carefully as well. (Keys et al., 2010) exploit a specific rule of thumb that determines the ease of mortgage securitization to show that mortgages that are easier to securitize are 10%-25% more likely to result in delinquency or foreclosure than mortgages that are difficult to securitize. Non-banks rely on securitization more than banks: they keep on average 20% of originated mortgages on their balance sheets whereas banks sell about 50 percent of their loans in the agency securitization market. It follows that the adopted originate-to-distribute lending model reduces non-banks' incentives to screen borrowers more than banks' incentives. Another source of misaligned incentives in the non-bank sector could be widespread commission-based broker fees (Rose, 2012).

The impact of regulation on banks and non-banks since the Great Recession has been analyzed in Buchak et al. (2018). The study shows that tighter regulation of mortgage origination and servicing activities led to a reduced role of traditional banks in residential mortgage markets where they faced more regulatory constraints. Non-banks partially replaced traditional banks in those markets, explaining a rapid growth of non-bank mortgage credit since the end of the crisis. Our paper acknowledges the increased role of non-banks in the residential mortgage market. We investigate whether the increase in the median foreclosure probability is associated with the less regulated financial institutions only – non-banks. We find, however,

[4] The extent of results are somewhat limited because the study does not include the foreclosure crisis in the data and analyzes delinquencies among securitized loans only. The alternative though unproved explanation is that banks securitize worse quality loans to keep better quality loans on their balance sheets.

that the median foreclosure probability remained higher in both the bank sector and the non-bank sector.

Finally, an emerging body of literature has focused on the vulnerability of non-banks with respect to liquidity risk (Kim et al., 2018). The non-banks' funding structure makes them especially prone to counterparty runs and although non-banks are not depository institutions, they eventually may shift the risk to taxpayers. The last crisis showed that the government may decide to bail out financial institutions beyond its explicit mandate, if they pose significant systemic risk. The literature has devoted much less attention to the triggers of non-bank liquidity risk, the foreclosure probability of mortgages originated or serviced by non-banks being one of them. This paper fills in this gap by examining foreclosure risk among non-bank borrowers and its implications to the mortgage market in the US.

2 Data and Results

This section reports the results of foreclosure probability estimation in 2007-2009 and the prediction of foreclosure probabilities in 2010-2016. In subsection 2.1 we describe the SCF structure and compare mortgage borrower characteristics over different years. In subsection 2.2 we report the estimation results. Subsection 2.3 reports how the distribution of predicted foreclosure probabilities changed over time and discusses its implication.

2.1 Data

The SCF is a cross-sectional triennial survey conducted by the Federal Reserve Board. The survey provides detailed financial and demographic information of the US households. Although the sample size of the SCF is between 4000 - 6000 in each wave, the survey weights make the analysis nationally representative. The sample foreclosure rate is 2.3%. Our estimate is slightly higher that the national foreclosure rate of 2% in 2009 because we count foreclosures over the period 2007-2009.[5] The survey distinguishes between lender types. We use this information to classify mortgages by lender types. We define a mortgage as a non-bank mortgage, if it was originated by a non-bank.

Table 1 provides the demographic and financial characteristics of mortgage borrowers in 2007 and 2016.[6] The SCF corrects for missing values using multiple imputation (Kennickell, 1998). To account for this multiple imputation in generating sample means or medians, weights are divided by 5 as suggested in the SCF codebook. All statistics are computed using analytic weights to make them representative of the population statistics. Finally, all dollar values are converted to USD dollars in 2016.

There are no large differences in demographic and financial characteristics, if we compare the full sample of mortgage borrowers between 2007 and 2016. Borrowers in 2016 were more likely to have higher education, to be single and earn more. Due to higher median income, median debt service to income (DSTI) ratio was lower in 2016 than in 2007. Borrowers were less likely to have missed payments or be turned down for credit

[5] CoreLogic, Inc. "10-Year Foreclosure Crisis Recap -CoreLogic", Mar 14 2017, available at `http://www.mortgagenewsdaily.com/03142017_corelogic_foreclosures.asp`.

[6] Due to space considerations, the same characteristics for households in 2010 and 2013 are provided in Appendix Tables 4 and 5.

in the past 12 months. Other financial characteristics reflected negative changes over time: in 2016 median net worth was lower and median loan to value (LTV) ratio higher.

We also split the sample between mortgages held with banks and non-banks. The share of non-bank mortgages to total mortgages in 2016 in our sample is 42%. Splitting the sample by lender type reveals significant differences conditional on lender type. Conforming with Kim et al. (2018), African-Americans, Hispanics, individuals with lower education, lower mean income and net worth are more likely to be associated with non-banks. Also, non-bank borrowers have higher LTV ratio and DSTI ratio. For instance, in 2016 non-bank borrowers have 12 percentage points higher median LTV ratio than median full-sample LTV ratio in 2007. Their net worth is almost $84,000 lower than median full-sample income in 2016.

Although the SCF provides a limited set of information about loan characteristics, we nevertheless analyze the differences in loan characteristics by lender type. Table 1 in provides the loan characteristics of mortgage borrowers in 2007 and 2016. The loan characteristics include an indicator for adjustable/fixed interest rate, for whether insured by FHA/VA, whether the mortgage has an option to be converted to a mortgage with a fixed interest rate without having to refinance it (convertible mortgage), whether repayment is scheduled as regular payments or with a balloon payment and original interest rate. These characteristic reiterate the previous finding that that non-bank mortgages tend to be taken by riskier borrowers, because they need government insurance (FHA/VA) rather GSEs insurance and they are priced as riskier as suggested by higher original interest rates. In addition to that, this table also suggests that mortgage type itself can give rise to higher default risk among non-bank borrowers: non-bank mortgages tend to have adjustable interest rates rather than fixed interest rates, balloon payments rather than regular payments and they are less likely to be convertible. In 2016 most of the characteristics suggest a decrease in risky loan taking, for instance, there are fewer mortgages with adjustable interest rates or balloon payments.

2.2 Foreclosure Probability Models and Estimation

Although the SCF is a cross-section survey, in 2009, to gauge the impact of the Great Recession on household balance sheet, households interviewed in 2007 were re-interviewed. This re-interview allows us to track households who held a mortgage in the 2007 survey but reported foreclosure in the 2009 survey. Using this information we estimate a foreclosure probability model in which the dependent variable is an indicator variable of foreclosure and independent variables are household financial and demographic characteristics.

For demographic characteristics we use dummies for race, education attainment, marital status and a quadratic function of age in years. The financial characteristics include indicators of unemployment during last 12 months, ownership of other residential real estate, second mortgage, mortgage guaranteed by Federal Housing Agency (FHA) or U.S. Department of Veteran Affairs (VA), missed mortgage payments, rejected credit applications in past five years, adjustable interest rate of the first or second mortgage, and if the mortgage was ever refinanced.[7] For continuous financial characteristics variables we include DSTI ratio,

[7]The 2007 SCF asks whether a respondent was turned down for credit in the last 2 years. After 2007 this question changes to whether in the last 12 months any lender turned down a respondent's credit application. Similarly, in 2007 the SCF asks whether in the last 5 years a respondent did not apply for credit for the fear of being rejected. In 2016 this question changes to whether in the last 12 months a respondent did not apply for credit for the fear of being rejected. It follows that we may overestimate the

current LTV ratio, a log of house value, total household net worth and a quadratic function of mortgage age.

In choosing these variables we follow the large literature on foreclosure models. Bayer et al. (2016) emphasize that minorities are more vulnerable to default on their mortgages. Elul et al. (2010); Gerardi et al. (2017); Gyourko and Tracy (2014) outline the importance of liquidity in foreclosure. We capture the liquidity using unemployment spell in the last year[8], net worth, DSTI[9] and whether declined for credit in the past five years. By using whether denied for credit in the past five years we capture household credit rating which is an important predictor of foreclosure probability (Demyanyk and Van Hemert, 2009). Further, Ferreira and Gyourko (2015) show that current LTV, a proxy for negative equity, is a dominant factor in the determination of foreclosure. Also, LTV's effect can be nonlinear. Following Ferreira and Gyourko (2015) we include two specifications of LTV. In the first specification, we only include the level of LTV and in the second specification we use dummies for different intervals of LTV. Speculative behavior can determine foreclosure (Haughwout et al., 2011). We capture speculative behavior using the dummy for owning more than one residential real estate.

In Table 2 we report the results of estimating the foreclosure probability in 2007-2009 with selected variables. For estimation we use two methods: a probit model, column (1)-(2), and a logit model, columns (3)-(4). With each method we estimate two types of models. The baseline model, columns (1) and (3), includes the LTV ratio in a linear form. The extended model, columns (2) and (4), includes the LTV ratio transformed into three intervals for estimation purposes: 0:0.25, 0.25:0.5, 0.5:0.75 and above 0.75. Focusing on the results from the probit model, our results largely confirm the existing literature on predicting foreclosure. For instance, current LTV ratio is one of the most important foreclosure drivers (e.g. Ferreira and Gyourko (2015)). Including LTV non-linearly (column (2)) shows that the effect stems from the highest values of LTV ratio: LTV ratio higher than 0.75 has the largest significant effect on foreclosure. African-Americans and Hispanics are more susceptible to foreclosure. The race effect is of similar size as having a second residential property. Further, as expected unemployment in the last year plays an important role in choosing foreclosure. The estimated McFadden's pseudo R^2 is higher than in similar models (e.g. Keys et al. (2009)). Similar results are obtained from logit models. For further analysis we use the baseline specification presented in column (1) because it has the largest explanatory power.

2.3 Predicted Foreclosure Probabilities

In this section we report and discuss the predicted foreclosure probabilities. Using coefficients obtained by fitting the probit model in Table 2 column (1), along with demographic and financial characteristics of respective years and survey weights, we predict foreclosure probabilities for years 2007, 2010, 2013 and 2016.

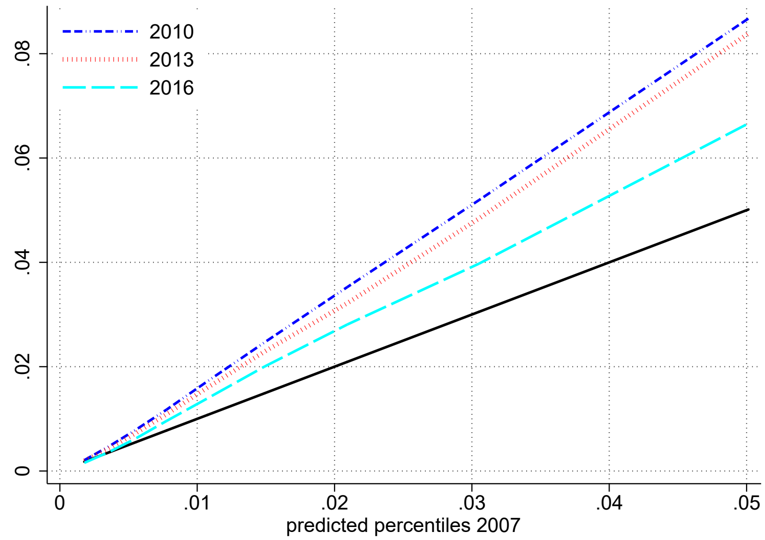
Figure 1 plots percentiles of predicted foreclosure probabilities for years 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities of the benchmark year 2007. The solid 45 degree line plots percentiles of foreclosure probability in 2007 against themselves, creating a 45° line. All percentile values

contribution of credit rejection or fear of being rejected in predicting foreclosure risk after 2007. However, as model estimation shows the role of these factors is fairly limited, so the overestimation bias is negligible.

[8](Gerardi et al., 2017) establish that job loss has an equivalent effect on default likelihood as a 35 percent decline in equity.

[9]Fuster and Willen (2017) find that an interest rate reduction by 3 p.p. has similar results as 45 p.p. lower cumulative LTV.

Figure 1: Predicted Percentiles



Notes: This figure plots percentiles of predicted foreclosure probabilities in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, Column 1). The percentiles are computed using 100 equidistant points and survey analysis weights.

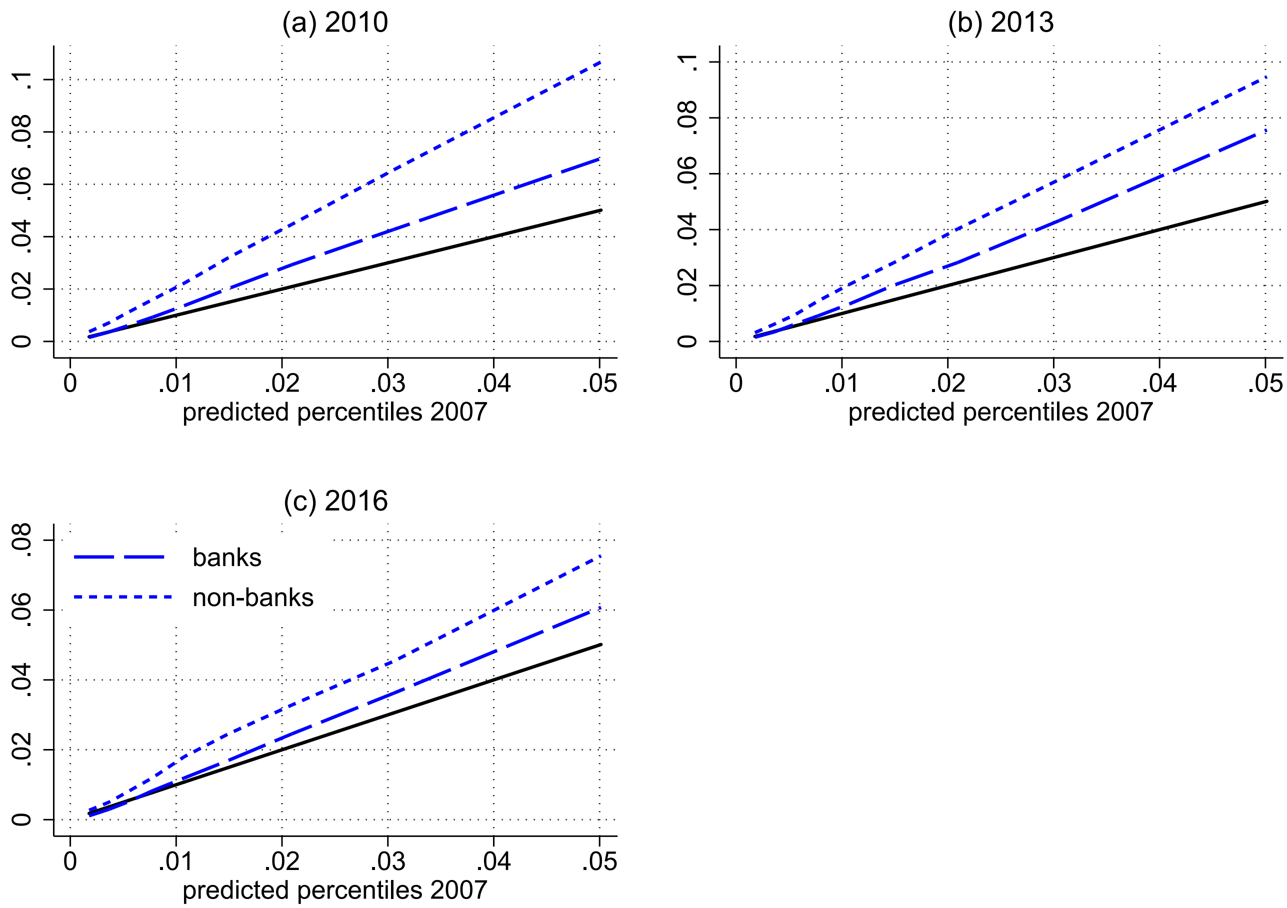
in years since 2007 are higher relative to values in 2007: all lines are above the 45° line. The difference is decreasing over time but even in 2016 foreclosure probabilities are still higher than before the crisis. We obtain this result in an environment with improving risk profile of bank borrowers and increasing housing prices that makes it the lower-bar estimate of foreclosure risk in the US residential mortgage market. To ascertain the role of non-banks, we repeat the same exercise conditional on lender type. Figure 2 reports these results. Non-bank borrowers stand out as riskier borrowers for all years and the distance from their foreclosure risk to total foreclosure risk in 2007 has slightly diminished. The percentile values for bank borrowers, on the other hand, got closer to the values in 2007 over time.

The results do not change, if we restrict the sample to mortgages issued or refinanced after 2008 or if we include an indicator for lender type in the foreclosure probability model. These robustness checks are presented in more detail in section 3.

Selected percentile values from the distribution of predicted foreclosure probability reveal more details about changes of foreclosure risk over time. Table 3 presents percentile values by lender type and over time. Based on the percentile values, mortgage borrowers contained the highest foreclosure risk in 2010 which matches the apogee of the foreclosure crisis. Although foreclosure probability has followed a downward trend since 2010, in 2016 the median foreclosure probability was still 27% (0.3 percentage points) higher than in 2007.

Foreclosure risk varies by lender type substantially. In 2016 the median foreclosure probability for bank borrowers was the same as the median foreclosure probability for the full-sample in 2007. Only the values of the 75th and 95th percentiles in 2016 remained higher above their full-sample counterparts from the

Figure 2: Predicted Percentiles by Lender Type

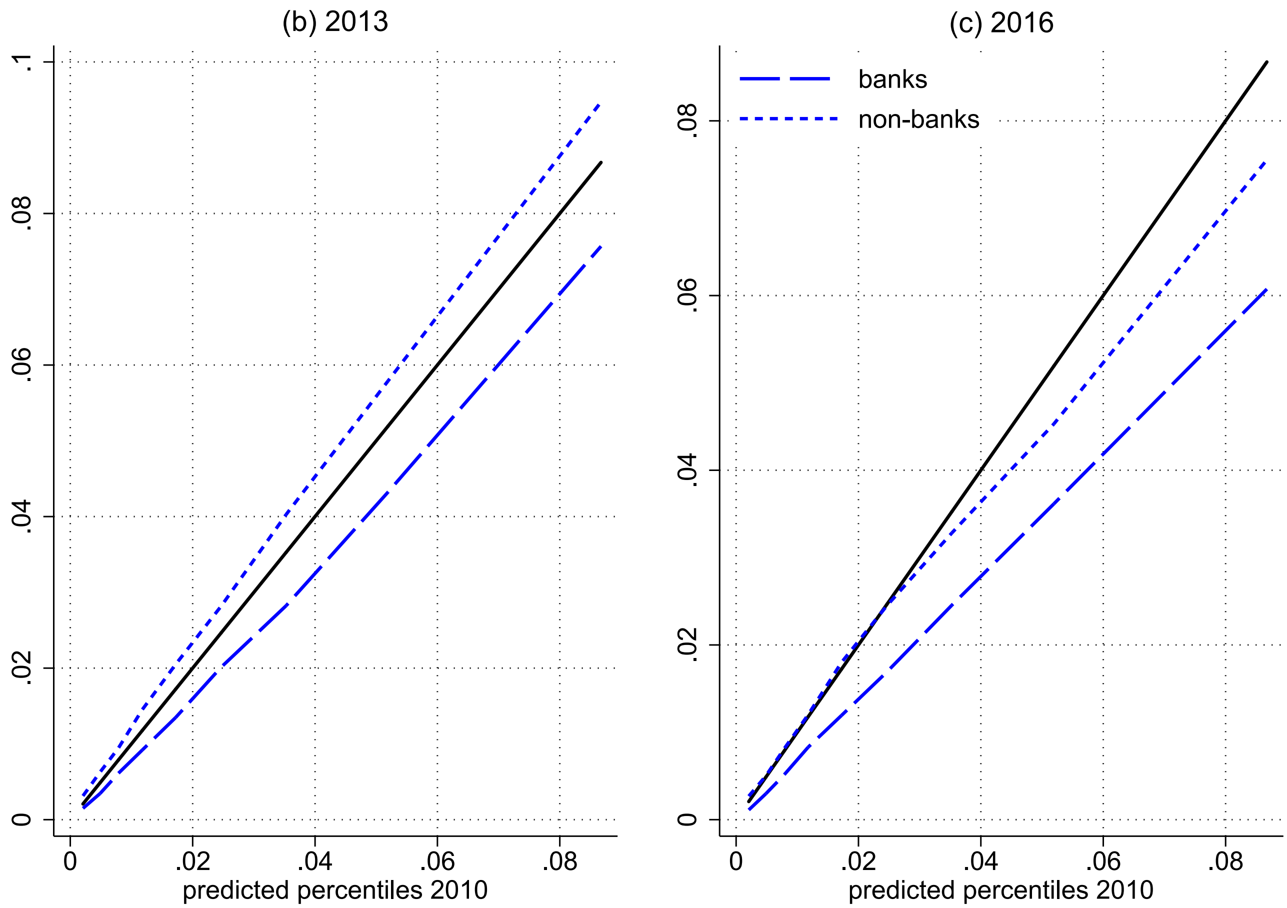


Notes: This figure plots percentiles of predicted foreclosure probabilities, conditional on lender type, in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, Column 1). The percentiles are computed using 100 equidistant points and survey analysis weights.

2007 sample, suggesting that risk in the right-tail of the distribution has not subsided completely. However, all percentile values for non-bank borrowers remained elevated above percentile values of the full-sample distribution in 2007. For instance, the median foreclosure probability for non-bank borrowers remained 64% (or 0.7 percentage points) higher than the median foreclosure probability for the full-sample in 2007.

Despite the fact that the median foreclosure probability for bank borrowers in 2016 was the same as the median foreclosure probability for the full-sample before the crisis, foreclosure risk remained elevated in both non-bank and bank sectors compared to foreclosure risk in those sectors before the crisis. The median foreclosure probability for bank borrowers in 2016 was 50% (0.4 percentage points) higher than in 2007. Compared to non-bank mortgages in 2007, non-bank mortgages remained 38.5% more likely (or 0.5 percentage points) to foreclose. Non-bank borrowers also remained significantly riskier on average than bank borrowers. Across all percentiles in 2016, estimated foreclosure probabilities of non-bank borrowers were at

Figure 3: Predicted Percentiles by Lender Type



Notes: This figure plots percentiles of predicted foreclosure probabilities, conditional on lender type, in 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2010. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, Column 1). The percentiles are computed using 100 equidistant points and survey analysis weights.

least 20% higher than the respective probabilities for bank-borrowers.

Looking at the distribution of foreclosure risk in 2016, we document that foreclosure risk in the non-bank sector had significant implications for the whole residential mortgage market. We infer this from the finding that non-bank mortgages had substantially riskier characteristics than in 2007 and thus contributed to a median mortgage in 2016 being more risky based on individual characteristics than in 2007. With this data we cannot analyze the relative contribution of non-bank mortgages to higher foreclosure risk in 2016 in more detail, but our results show that bank mortgages contributed to a median mortgage in 2016 being more risky based on individual characteristics than in 2007 as well, although on average bank mortgages were substantially less risky than non-bank mortgages.

2.4 Are the regulatory effects visible?

Main regulatory changes that contributed to the rise of non-banks (Buchak et al., 2018) took place after 2010. For instance, the US regulatory agencies issued the final rule on Basel III risk-based capital in 2013 and brought it into force on 1 January 2014 (Bank for International Settlements, 2014). The period after 2010 also contained the establishment of the Consumer Financial Protection Bureau, the dissolution of the Office of Thrift Supervision and other decisions coming from the implementation of the Dodd-Frank Act. Therefore, the potential effects of the regulatory tightening could not be observed before 2010. To that end, in this section we compare foreclosure risk in 2013 and 2016 to predicted foreclosure probabilities in 2010.

Figure 1 shows a decline in predicted foreclosure probabilities compared to 2010. To describe risk patterns in the bank sector and the non-bank sector separately, we produce a new figure, that is Figure 3. Figure 3 plots percentiles of predicted foreclosure probabilities for years 2013 and 2016 for banks and non-banks against the full-sample percentiles of predicted foreclosure probabilities in 2010. We observe that in 2013 non-bank mortgages carried riskier characteristics than average risk characteristics in 2010, but in 2016 foreclosure probabilities for non-bank mortgages were lower than average foreclosure probabilities in 2010 across the whole distribution. Bank mortgages both in 2013 and 2016 carried lower foreclosure probabilities than the full-sample in 2010. This suggests that both bank and non-banks mortgages have become safer compared to 2010., but to a different extent. We conjecture that the regulatory change that targeted mainly banks rather than non-banks should produce a higher decline in risk among bank mortgages rather than non-bank mortgages. So in the next paragraph we compare the rate of decline in foreclosure risk by lender type.

To compare the distribution moments of foreclosure risk by lender type over time, we refer again to Table 3. The higher decline in risk among bank mortgages compared to non-bank mortgages would be the expected result of the regulatory change that targeted mainly banks rather than non-banks. However, we observe that the regulatory change might have played a smaller role in foreclosure dynamics than expected because foreclosure risk was decreasing faster in the non-bank segment of the market rather than the bank segment. Compared to 2010, the median foreclosure probability for non-bank mortgages declined by 18.2% (or 0.4 percentage points) by 2016, but the median foreclosure probability for bank mortgages declined by 14.3% (or 0.2 percentage points).

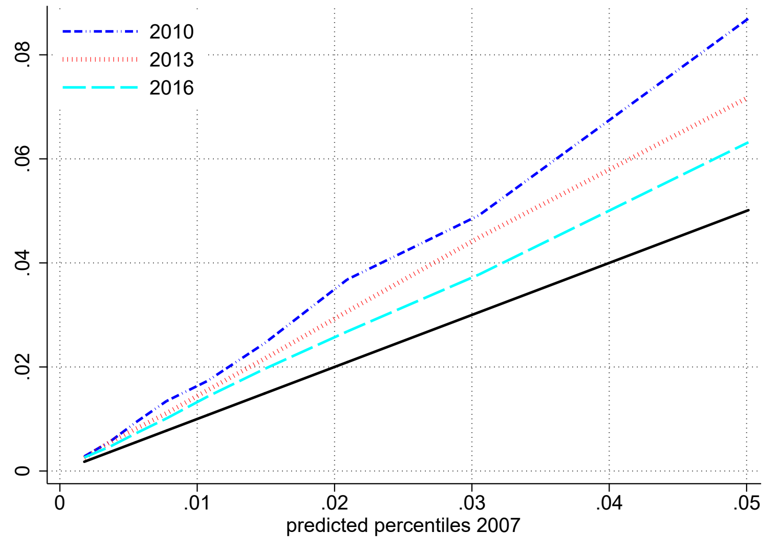
Therefore, after 2010 foreclosure risk started declining for all mortgages, but bank mortgages have not necessarily become less risky compared to non-bank mortgages. The regulatory effect on foreclosure risk thus might have played a weaker effect than expected. It suggests that the effectiveness of regulatory changes requires a thorough analysis, accounting for different borrower segments and aggregate trends.

3 Robustness checks

3.1 Role of Legacy Mortgages

In this section we show that our results are not dominated by legacy mortgages but capture lenders' response after the crisis too. We already account for different mortgage cohorts by including mortgage age as an explanatory variable in the foreclosure probability model, but this may not be sufficient to take into account

Figure 4: Predicted Percentiles: Mortgages Issued or Refinanced after 2008



Notes: This figure plots percentiles of predicted foreclosure probabilities for new mortgages in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, column (1)). The percentiles are computed using 10 equidistant points and survey analysis weights.

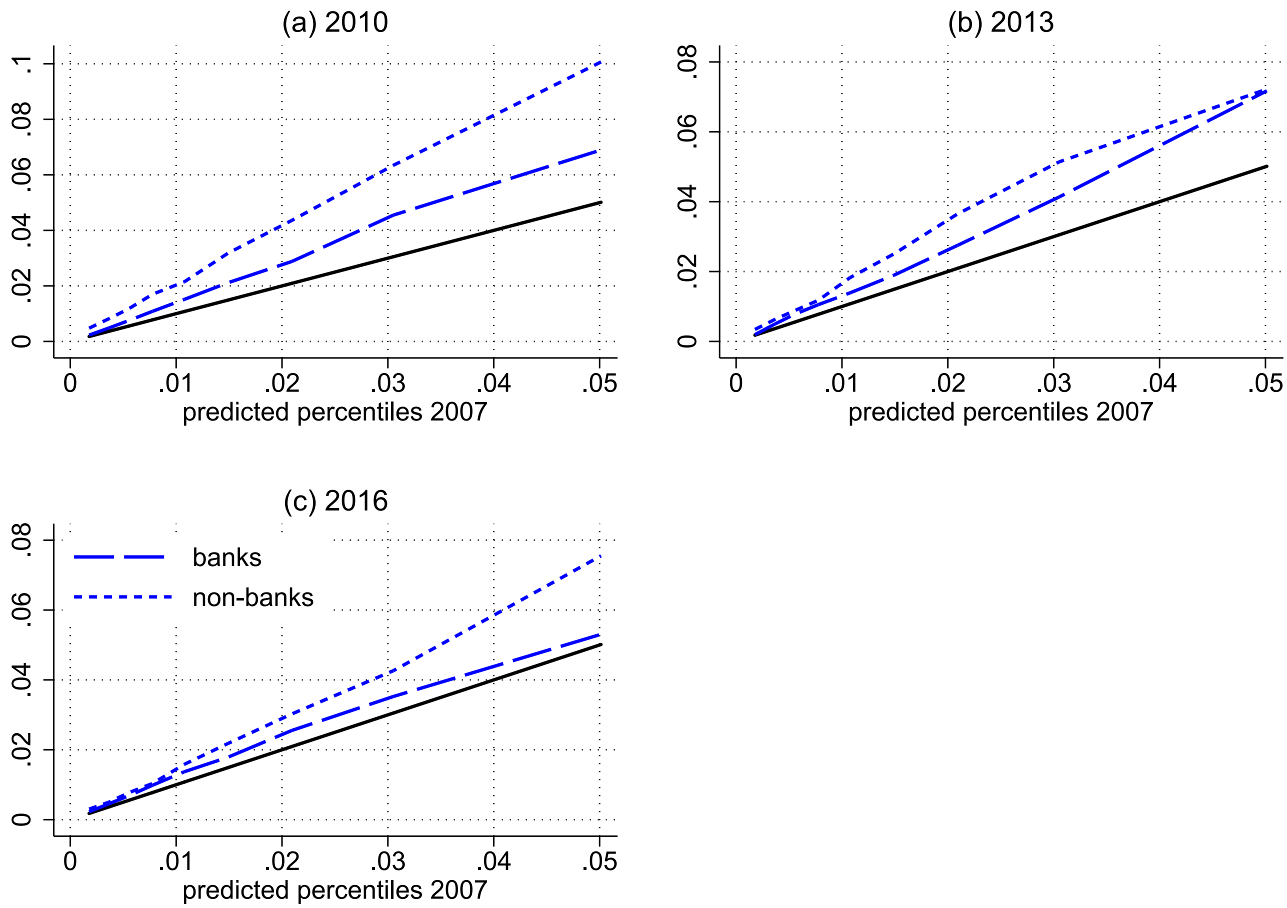
that lenders could alter their lending behavior, e.g. respond to changes in regulation, by changing new contracts only. Thus, remaining old (risky) mortgages may give an impression that foreclosure risk has remained the same, although after the crisis banks may have started issuing substantially less risky mortgages. To address this concern, we repeat previous exercises with mortgages issued or refinanced after 2008 only.[10]

The results, obtained using the same method as above, confirm our previous results from the full mortgage sample. To avoid repetition, the demographic and financial characteristics of new mortgage borrowers as well as estimates from the foreclosure model are provided in Appendix Tables 6-8. Using the estimates from the foreclosure probability model, foreclosure probabilities are predicted for new mortgages in 2010, 2013 and 2016. Figure 4 has a pattern that is similar to Figure 1: all percentile values in subsequent waves since 2007 are higher but follow a decreasing trend. Decomposition of percentile values based on lender type also provide similar results as is shown in Figure 5: Bank borrowers were similar in terms of risk to average and median borrowers in 2007, whereas mortgages associated with non-banks carried substantially higher foreclosure risk. Hence, new non-bank mortgages continued shifting the total foreclosure risk distribution to the right.

Taking year 2010 instead of 2007 as a benchmark, we attempt to make a non-causal statement about the regulatory effects on risk. We observe that the regulatory change might have played a smaller role in foreclosure dynamics than expected because as in the baseline specification, foreclosure risk was decreasing faster in the non-bank segment of the market rather than the bank segment. Table 9 in Appendix shows that, compared to 2010, the median foreclosure probability for non-bank mortgages issued or refinanced after 2008 declined by 23.8% (or 0.5 percentage points) by 2016, but the median foreclosure probability for bank

[10]The SCF data does not allow to distinguish between origination and refinancing dates, so new mortgages here can mean both newly originated and newly refinanced mortgages.

Figure 5: Predicted Percentiles by Lender Type: Mortgages Issued or Refinanced after 2008



Notes: This figure plots percentiles of predicted foreclosure probabilities for new mortgages, conditional on lender type, in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, column (1)). The percentiles are computed using 10 equidistant points and survey analysis weights.

mortgages declined by 6.7% (or 0.1 percentage points). The regulatory effect on foreclosure risk thus might have played a weaker effect than aggregate shocks in driving foreclosure risk down.

3.2 Role of the Lender Indicator

The large literature shows that banks screen applicants more thoroughly than non-banks and this can partially explain the foreclosure risk difference (e.g. Alexander et al. (2002)). However, the difference between screening efforts must have changed since 2007. For instance, changes in regulation since 2007 should have affected screening efforts in the banking sector more, so by using the 2007 estimate of the bank lender effect, we may overestimate foreclosure risk for bank mortgages in 2016. Therefore, in the baseline specification we predict foreclosure risk from factors that do not change with regulations, i.e. borrowers' characteristics. In this section we estimate a probit model with an indicator for lender type. Results generated by this exercise show that the inclusion of the lender indicator does not have a significant bearing on our results.

The estimation results presented in Appendix Table 10 conform with the literature: we show that non-bank mortgages were more likely to foreclose in 2007 than bank mortgages and that the effect is significant. Using these new estimates we predict foreclosure probabilities and plot their percentiles in Figures 6 and 7. We also show the resulting percentile values of the foreclosure risk distribution in Appendix Table 11. The results are qualitatively the same as in the baseline specification. In 2016 the median foreclosure probability was 20% higher than in 2007. Mortgages associated with banks experienced decreasing foreclosure risk since 2010 and foreclosure probabilities in 2016 were even below the full-sample percentile values in 2007. Also, foreclosure risk of bank mortgages was always substantially lower than foreclosure risk of non-bank mortgages. This result is strengthened by the fact that our model does not capture regulatory environment changes and in turn overestimates foreclosure risk for bank-mortgages after 2007.

4 Concluding Remarks

This paper examines how foreclosure risk changed in the US since the foreclosure crisis. We show that a representative sample of US mortgage borrowers had more risky individual characteristics in 2016 than in 2007. Thus, if the aggregate shocks of 2008-2009 repeated in 2016, foreclosure rate would be higher than in 2010. Both non-bank mortgages and bank mortgages had substantially riskier characteristics in 2016 than in 2007.

This analysis cannot provide an answer to what made lenders choose mortgage borrowers with risky characteristics. The peak of the foreclosure crisis in 2010 coincides with the start of regulatory reforms, so we cannot distinguish the role of aggregate shocks from the role of regulatory changes. However, our analysis offers insights that motivate the need to analyze the regulatory effects explicitly. We find that although aggregate predicted foreclosure risk was decreasing after 2010, it was not decreasing faster in the market segment that was affected more by the regulatory changes. We find that over the period 2010-2016 predicted foreclosure probabilities declined faster for non-bank mortgages rather than bank mortgages. Therefore, the regulatory effects were either not strong enough to outweigh aggregate shocks or had unexpected effects on lending standards across the market. A more thorough analysis of the effectiveness of regulation would contribute to this discussion substantially.

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Table 1: Mortgage Borrowers' Characteristics in 2007 and 2016

Survey year:	2007			2016		
Lender:	All (1)	Non-banks (2)	Banks (3)	All (4)	Non-banks (5)	Banks (6)
Demographic characteristics						
White	0.787	0.751	0.825	0.751	0.722	0.77
	(0.41)	(0.433)	(0.38)	(0.433)	(0.448)	(0.421)
Black	0.101	0.135	0.065	0.118	0.128	0.112
	(0.302)	(0.342)	(0.246)	(0.323)	(0.334)	(0.315)
Hispanic	0.112	0.114	0.11	0.131	0.15	0.118
	(0.316)	(0.317)	(0.313)	(0.337)	(0.357)	(0.323)
Age $\leq$ 65	0.893	0.925	0.858	0.814	0.842	0.795
	(0.309)	(0.264)	(0.349)	(0.389)	(0.365)	(0.404)
Less than high school	0.373	0.375	0.371	0.303	0.333	0.282
	(0.484)	(0.484)	(0.483)	(0.46)	(0.471)	(0.45)
Above high school	0.627	0.625	0.629	0.697	0.667	0.718
	(0.484)	(0.484)	(0.483)	(0.46)	(0.471)	(0.45)
Married	0.734	0.742	0.725	0.717	0.716	0.717
	(0.442)	(0.437)	(0.447)	(0.451)	(0.451)	(0.45)
Financial characteristics						
Median net worth	229,644	178,330	270,395	190,606	145,672	225,166
	(2,402,956)	(1,857,609)	(2,870,204)	(3,473,580)	(2,062,343)	(4,163,466)
Mean household income	111,384	102,121	121,352	135,356	109,189	153,445
	(267,684)	(172,994)	(341,158)	(407,225)	(166,577)	(510,392)
Median household income	74,548	75,613	73483	80587	75673	84518
	(267,684)	(172,994)	(341,158)	(407,225)	(166,577)	(510,392)
Median LTV	0.494	0.579	0.4	0.553	0.623	0.506
	(0.27)	(0.242)	(0.274)	(0.278)	(0.256)	(0.284)
Median DSTI	0.251	0.266	0.231	0.215	0.231	0.2
	(1.592)	(1.219)	(1.914)	(1.88)	(1.404)	(2.148)
Turned down for credit	0.155	0.187	0.12	0.091	0.102	0.084
	(0.362)	(0.39)	(0.325)	(0.288)	(0.303)	(0.277)
Did not apply for credit	0.024	0.034	0.014	0.031	0.045	0.021
	(0.154)	(0.181)	(0.116)	(0.172)	(0.207)	(0.143)
% Missed payments	0.102	0.135	0.066	0.061	0.077	0.051
	(0.303)	(0.342)	(0.248)	(0.24)	(0.266)	(0.219)
Loan characteristics						
Adjustable interest rate	0.15	0.159	0.141	0.072	0.063	0.078
	(0.357)	(0.365)	(0.348)	(0.259)	(0.243)	(0.269)
FHA/VA guarantee	0.203	0.224	0.18	0.318	0.341	0.302
	(0.402)	(0.417)	(0.384)	(0.466)	(0.474)	(0.459)
Original interest rate	5.821	6.008	5.624	5.644	5.34	5.852
	(1.87)	(2.025)	(1.673)	(2.87)	(2.914)	(2.825)
Convertible mortgage	0.03	0.027	0.033	0.012	0.01	0.013
	(0.171)	(0.163)	(0.179)	(0.107)	(0.1)	(0.111)
Balloon payment	0.046	0.05	0.041	0.035	0.041	0.031
	(0.209)	(0.218)	(0.199)	(0.183)	(0.198)	(0.173)
N	1,982	904	1,078	2,590	946	1,644

Source: Survey of Consumer Finances (SCF), 2007 and 2016 wave. Standard deviations are in parentheses. To account for multiple imputation, survey weights are divided by 5. Acronyms: LTV: loan-to-value, DSTI: debt service to income, FHA guarante: guarantee by the US Federal Housing Administration mortgage insurance, VA guarante: guarantee by the Veterans Administration.

Table 2: Foreclosure Model Estimation

Dependent variable:	Foreclosure in 2007-2009			
Estimation method:	Probit		Logit	
	(1)	(2)	(3)	(4)
African-American	0.386**	0.423**	0.860**	0.943**
	(0.183)	(0.190)	(0.414)	(0.432)
Hispanic	0.367	0.407	0.879	0.951
	(0.309)	(0.267)	(0.719)	(0.623)
Married	-0.242*	-0.230*	-0.466	-0.458
	(0.145)	(0.135)	(0.326)	(0.307)
College degree	0.075	0.099	0.286	0.327
	(0.183)	(0.175)	(0.454)	(0.440)
Unemployed in last year	0.361**	0.348**	0.741*	0.722*
	(0.179)	(0.167)	(0.413)	(0.394)
DSTI ratio	0.035	0.033	0.076	0.062
	(0.083)	(0.037)	(0.183)	(0.085)
Has other residential RE	0.518***	0.534***	1.106***	1.159***
	(0.176)	(0.168)	(0.413)	(0.389)
FHA/VA	0.194	0.214	0.464	0.518
	(0.213)	(0.215)	(0.484)	(0.502)
Missed payments	0.559	0.564	1.003	1.023
	(0.620)	(0.414)	(1.648)	(0.882)
Turned down for credit	-0.004	0.019	0.028	0.081
	(0.200)	(0.197)	(0.457)	(0.451)
Log house value	-0.031	-0.055	-0.085	-0.145
	(0.102)	(0.087)	(0.234)	(0.201)
LTV	1.085***		2.701***	
	(0.400)		(0.910)	
$0.25 \leq$ LTV < 0.5		0.183		0.460
		(0.292)		(0.729)
$0.5 \leq$ LTV < 0.75		0.354		0.840
		(0.258)		(0.629)
LTV ≥ 0.75		0.471*		1.130*
		(0.282)		(0.675)
Pseudo R^2	0.197	0.170	0.196	0.166
N	1,982	1,982	1,982	1,982

Source: Survey of Consumer Finances 2007-2009 panel. STATA program *scfcombo* from Pence (2015) is used to account for imputation uncertainty and compute bootstrapped standard errors. Number of bootstraps is set equal to 200. Standard errors are reported in parentheses.

Table 3: Percentile Values of Predicted Foreclosure Probability Distribution

Survey year:	2007			2010			2013			2016		
Lender:	All (1)	Non-banks (2)	Banks (3)	All (4)	Non-banks (5)	Banks (6)	All (7)	Non-banks (8)	Banks (9)	All (10)	Non-banks (11)	Banks (12)
Mean	0.022	0.026	0.017	0.035	0.043	0.029	0.033	0.039	0.030	0.027	0.031	0.024
p(25)	0.005	0.006	0.003	0.006	0.009	0.005	0.006	0.008	0.005	0.005	0.006	0.004
p(50)	0.011	0.013	0.008	0.017	0.022	0.014	0.016	0.021	0.013	0.014	0.018	0.012
p(75)	0.025	0.030	0.020	0.042	0.053	0.035	0.040	0.049	0.034	0.034	0.038	0.030
p(95)	0.075	0.089	0.062	0.128	0.161	0.104	0.126	0.133	0.118	0.096	0.113	0.087
N	1,982	904	1,078	2,886	1,757	1,900	2,509	880	1,629	2,590	946	1,644

Notes: This table reports selected percentile values of foreclosure probability distribution in base year 2007 and in years 2010, 2013 and 2016. In each survey year we report unconditional percentile values (columns (1), (4), (7), (10)), whereas the rest of the columns report percentile values conditional on lender type i.e. banks and non-banks.

Appendix

Table 4: Mortgage Borrowers' Demographic Characteristics

Survey year:	2007			2010			2013			2016		
Lender:	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
White	0.787	0.751	0.825	0.776	0.747	0.797	0.782	0.761	0.795	0.751	0.722	0.77
	(0.41)	(0.433)	(0.38)	(0.417)	(0.435)	(0.402)	(0.413)	(0.427)	(0.404)	(0.433)	(0.448)	(0.421)
Black	0.101	0.135	0.065	0.095	0.122	0.074	0.103	0.119	0.092	0.118	0.128	0.112
	(0.302)	(0.342)	(0.246)	(0.293)	(0.327)	(0.262)	(0.303)	(0.324)	(0.289)	(0.323)	(0.334)	(0.315)
Hispanic	0.112	0.114	0.11	0.13	0.131	0.129	0.116	0.12	0.114	0.131	0.15	0.118
	(0.316)	(0.317)	(0.313)	(0.336)	(0.337)	(0.335)	(0.32)	(0.325)	(0.317)	(0.337)	(0.357)	(0.323)
Age $\leq$ 65	0.893	0.925	0.858	0.859	0.898	0.829	0.843	0.856	0.835	0.814	0.842	0.795
	(0.309)	(0.264)	(0.349)	(0.349)	(0.303)	(0.376)	(0.364)	(0.351)	(0.371)	(0.389)	(0.365)	(0.404)
Less than high school	0.373	0.375	0.371	0.357	0.374	0.345	0.33	0.361	0.31	0.303	0.333	0.282
	(0.484)	(0.484)	(0.483)	(0.479)	(0.484)	(0.475)	(0.47)	(0.48)	(0.463)	(0.46)	(0.471)	(0.45)
Above high school	0.627	0.625	0.629	0.643	0.626	0.655	0.67	0.639	0.69	0.697	0.667	0.718
	(0.484)	(0.484)	(0.483)	(0.479)	(0.484)	(0.475)	(0.47)	(0.48)	(0.463)	(0.46)	(0.471)	(0.45)
Married	0.734	0.742	0.725	0.714	0.71	0.718	0.721	0.703	0.732	0.717	0.716	0.717
	(0.442)	(0.437)	(0.447)	(0.452)	(0.454)	(0.45)	(0.449)	(0.457)	(0.443)	(0.451)	(0.451)	(0.45)
Not married	0.266	0.258	0.275	0.286	0.29	0.282	0.279	0.297	0.268	0.283	0.284	0.283
	(0.442)	(0.437)	(0.447)	(0.452)	(0.454)	(0.45)	(0.449)	(0.457)	(0.443)	(0.451)	(0.451)	(0.45)
N	1,982	904	1,078	2,886	1,757	1,900	2,509	880	1,629	2,590	946	1,644

Source: Survey of Consumer Finances (SCF) 2007-2016. Standard deviations are in parentheses. To account for multiple imputation, survey weights are divided by 5. "Married" includes both married or living with a partner.

Table 5: Mortgage Borrowers' Financial Characteristics

Survey year:	2007			2010			2013			2016		
Lender:	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Median net worth	229644	178330	270395	149194	108785	189550	165113	121803	197015	190606	145672	225166
	(2402956)	(1857609)	(2870204)	(2265177)	(1711791)	(2591680)	(2160896)	(1703776)	(2399058)	(3473580)	(2062343)	(4163466)
Mean household income	111384	102121	121352	110077	98931	118391	119137	107295	126600	135356	109189	153445
	(267684)	(172994)	(341158)	(229896)	(132061)	(281261)	(340412)	(315148)	(355232)	(407225)	(166577)	(510392)
Median household income	74548	75613	73483	71945	70855	73035	76142	72081	79187	80587	75673	84518
	(267684)	(172994)	(341158)	(229896)	(132061)	(281261)	(340412)	(315148)	(355232)	(407225)	(166577)	(510392)
Median LTV	0.494	0.579	0.4	0.609	0.667	0.56	0.625	0.693	0.583	0.553	0.623	0.506
	(0.27)	(0.242)	(0.274)	(0.32)	(0.298)	(0.328)	(0.303)	(0.284)	(0.31)	(0.278)	(0.256)	(0.284)
% LTV > 90%	0.053	0.071	0.033	0.189	0.222	0.165	0.162	0.194	0.142	0.075	0.11	0.051
	(0.224)	(0.257)	(0.18)	(0.392)	(0.416)	(0.371)	(0.369)	(0.395)	(0.349)	(0.264)	(0.313)	(0.22)
% LTV > 95%	0.018	0.021	0.014	0.143	0.17	0.123	0.117	0.143	0.101	0.036	0.057	0.021
	(0.133)	(0.145)	(0.118)	(0.35)	(0.376)	(0.328)	(0.322)	(0.35)	(0.301)	(0.186)	(0.232)	(0.144)
Median DSTI	0.251	0.266	0.231	0.247	0.265	0.228	0.222	0.237	0.215	0.215	0.231	0.2
	(1.592)	(1.219)	(1.914)	(6.402)	(6.353)	(6.438)	(1.172)	(1.168)	(1.174)	(1.88)	(1.404)	(2.148)
Turned down for credit	0.155	0.187	0.12	0.181	0.216	0.154	0.165	0.183	0.154	0.091	0.102	0.084
	(0.362)	(0.39)	(0.325)	(0.385)	(0.412)	(0.361)	(0.371)	(0.386)	(0.361)	(0.288)	(0.303)	(0.277)
Did not apply for credit	0.024	0.034	0.014	0.053	0.077	0.036	0.043	0.054	0.036	0.031	0.045	0.021
	(0.154)	(0.181)	(0.116)	(0.224)	(0.266)	(0.185)	(0.203)	(0.227)	(0.186)	(0.172)	(0.207)	(0.143)
% Missed payments	0.102	0.135	0.066	0.148	0.19	0.117	0.135	0.176	0.109	0.061	0.077	0.051
	(0.303)	(0.342)	(0.248)	(0.355)	(0.392)	(0.321)	(0.342)	(0.381)	(0.312)	(0.24)	(0.266)	(0.219)
% changed a servicer	0.56	0.569	0.551	0.514	0.512	0.515	0.584	0.577	0.588	0.521	0.509	0.53
	(0.496)	(0.495)	(0.497)	(0.5)	(0.5)	(0.5)	(0.493)	(0.494)	(0.492)	(0.5)	(0.5)	(0.499)
Average loan age (years)	5.733	5.694	5.775	4.793	5.19	4.497	4.664	5.194	4.329	5.415	5.629	5.267
	(4.27)	(3.768)	(4.751)	(4.558)	(4.497)	(4.581)	(4.863)	(5.102)	(4.676)	(5.455)	(5.59)	(5.356)
N	1,982	904	1,078	2,886	1,757	1,900	2,509	880	1,629	2,590	946	1,644

Source: Survey of Consumer Finances (SCF) 2007-2016. Standard deviations are in parentheses. To account for multiple imputation, survey weights are divided by 5. Income and net worth are summed over all household members. "Turned down for credit" denotes a dummy variable that gets a value one if a respondent was turned down for credit. The variable "Did not apply for credit" is a dummy variable that gets value one if a respondent did not apply for credit for the fear of being rejected. Missed payments reflects if respondent is currently behind payments on the 1st or 2nd mortgage.
Acronyms: LTV: the loan-to-value, DSTI: debt service to income.

Table 6: Foreclosure Model Estimation

Dependent variable:	Foreclosure in 2007-2009			
Estimation method:	Probit		Logit	
	(1)	(2)	(3)	(4)
Age	0.103	0.095	0.243	0.218
	(0.109)	(0.098)	(0.267)	(0.244)
Age-squared	-0.106	-0.100	-0.242	-0.225
	(0.116)	(0.106)	(0.287)	(0.268)
African-American	0.386**	0.423**	0.860**	0.943**
	(0.183)	(0.190)	(0.414)	(0.432)
Hispanic	0.367	0.407	0.879	0.951
	(0.309)	(0.267)	(0.719)	(0.623)
Married	-0.242*	-0.230*	-0.466	-0.458
	(0.145)	(0.135)	(0.326)	(0.307)
Some college/college degree	0.075	0.099	0.286	0.327
	(0.183)	(0.175)	(0.454)	(0.440)
Unemployed in the last yr	0.361**	0.348**	0.741*	0.722*
	(0.179)	(0.167)	(0.413)	(0.394)
DSTI ratio	0.035	0.033	0.076	0.062
	(0.083)	(0.037)	(0.183)	(0.085)
Has other residential RE	0.518***	0.534***	1.106***	1.159***
	(0.176)	(0.168)	(0.413)	(0.389)
Adjustable rate mortgage	0.256	0.327	0.555	0.713
	(0.238)	(0.205)	(0.577)	(0.488)
FHA/VA	0.194	0.214	0.464	0.518
	(0.213)	(0.215)	(0.484)	(0.502)
Has 2nd/3rd mortgage	-0.223	-0.183	-0.630	-0.524
	(0.527)	(0.523)	(1.490)	(1.538)
Has refinanced	-0.148	-0.176	-0.317	-0.385
	(0.144)	(0.145)	(0.340)	(0.342)
Missed payments	0.559	0.564	1.003	1.023
	(0.620)	(0.414)	(1.648)	(0.882)
Turned down for credit	-0.004	0.019	0.028	0.081
	(0.200)	(0.197)	(0.457)	(0.451)
Net worth	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mortgage age	-0.006	-0.020	-0.020	-0.053
	(0.066)	(0.066)	(0.158)	(0.162)
Mortgage age-squared	0.001	0.001	0.004	0.004
	(0.004)	(0.004)	(0.010)	(0.011)
Log house value	-0.031	-0.055	-0.085	-0.145
	(0.102)	(0.087)	(0.234)	(0.201)
LTV	1.085***		2.701***	
	(0.400)		(0.910)	
$0.25 \leq$ LTV < 0.5		0.183		0.460
		(0.292)		(0.729)
$0.5 \leq$ LTV < 0.75		0.354		0.840
		(0.258)		(0.629)
LTV ≥ 0.75		0.471*		1.130*
		(0.282)		(0.675)
Pseudo R^2	0.197	0.170	0.196	0.166
N	1,982	1,982	1,982	1,982

Source: Survey of Consumer Finances 2007-2009 panel.
STATA program *scfcombo* from Pence (2015) is used to account for imputation uncertainty and compute bootstrapped standard errors. Number of bootstraps is set equal to 200. Standard errors are reported in parentheses.
Acronyms: LTV: the loan-to-value, DSTI: debt service to income.

Table 7: Mortgage Borrowers' Demographic Characteristics: Mortgages Issued or Refinanced after 2008

Survey year:	2007			2010			2013			2016		
Lender:	All (1)	Non-banks (2)	Banks (3)	All (4)	Non-banks (5)	Banks (6)	All (7)	Non-banks (8)	Banks (9)	All (10)	Non-banks (11)	Banks (12)
White	0.787	0.751	0.825	0.822	0.78	0.852	0.809	0.797	0.817	0.77	0.753	0.782
	(0.41)	(0.433)	(0.38)	(0.382)	(0.414)	(0.356)	(0.393)	(0.402)	(0.387)	(0.421)	(0.432)	(0.413)
Black	0.101	0.135	0.065	0.072	0.088	0.06	0.073	0.078	0.07	0.103	0.107	0.1
	(0.302)	(0.342)	(0.246)	(0.258)	(0.283)	(0.238)	(0.26)	(0.267)	(0.254)	(0.303)	(0.309)	(0.299)
Hispanic	0.112	0.114	0.11	0.106	0.132	0.088	0.118	0.125	0.114	0.128	0.141	0.118
	(0.316)	(0.317)	(0.313)	(0.308)	(0.339)	(0.283)	(0.323)	(0.331)	(0.317)	(0.334)	(0.348)	(0.323)
Age $\leq$ 65	0.893	0.925	0.858	0.902	0.932	0.881	0.878	0.894	0.868	0.86	0.86	0.859
	(0.309)	(0.264)	(0.349)	(0.297)	(0.252)	(0.324)	(0.327)	(0.308)	(0.339)	(0.348)	(0.347)	(0.348)
Less than high school	0.373	0.375	0.371	0.316	0.357	0.287	0.291	0.29	0.291	0.277	0.297	0.262
	(0.484)	(0.484)	(0.483)	(0.465)	(0.479)	(0.453)	(0.454)	(0.454)	(0.454)	(0.447)	(0.457)	(0.44)
Above high school	0.627	0.625	0.629	0.684	0.643	0.713	0.709	0.71	0.709	0.723	0.703	0.738
	(0.484)	(0.484)	(0.483)	(0.465)	(0.479)	(0.453)	(0.454)	(0.454)	(0.454)	(0.447)	(0.457)	(0.44)
Married	0.734	0.742	0.725	0.727	0.721	0.731	0.76	0.766	0.757	0.733	0.709	0.751
	(0.442)	(0.437)	(0.447)	(0.446)	(0.449)	(0.444)	(0.427)	(0.424)	(0.429)	(0.442)	(0.454)	(0.432)
Not married	0.266	0.258	0.275	0.273	0.279	0.269	0.24	0.234	0.243	0.267	0.291	0.249
	(0.442)	(0.437)	(0.447)	(0.446)	(0.449)	(0.444)	(0.427)	(0.424)	(0.429)	(0.442)	(0.454)	(0.432)
N	1,982	903	1,079	641	244	397	1,339	478	861	1,683	632	1,051

Source: Survey of Consumer Finances (SCF) 2007-2016. In the 2007 SCF we take the full sample, whereas in the subsequent waves we restrict the sample to mortgages issued or refinanced after 2008. Standard deviations are in parentheses. To account for multiple imputation, survey weights are divided by 5. "Married" includes both married or living with a partner.

Table 8: Mortgage Borrowers' Financial Characteristics: Mortgages Issued or Refinanced after 2008

Survey year:	2007			2010			2013			2016		
Lender:	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks	All	Non-banks	Banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Median net worth	229644	178330	270395	129799	102445	147499	176021	160210	189655	198564	155959	234007
	(2402956)	(1857609)	(2870204)	(1731261)	(1521547)	(1859544)	(2085748)	(1745317)	(2274441)	(3671023)	(2136860)	(4455653)
Mean household income	111384	102121	121352	110342	105423	113776	126147	119383	130472	150303	119437	172717
	(267684)	(172994)	(341158)	(163669)	(126872)	(185020)	(302009)	(350892)	(266046)	(467385)	(182841)	(592989)
Median household income	74548	75613	73483	75215	75215	75215	84264	84264	83248	87761	80587	91397
	(267684)	(172994)	(341158)	(163669)	(126872)	(185020)	(302009)	(350892)	(266046)	(467385)	(182841)	(592989)
Median LTV	0.494	0.579	0.4	0.733	0.771	0.704	0.685	0.72	0.65	0.597	0.637	0.566
	(0.27)	(0.242)	(0.274)	(0.274)	(0.268)	(0.276)	(0.261)	(0.253)	(0.264)	(0.236)	(0.237)	(0.234)
% LTV > 90%	0.053	0.071	0.033	0.27	0.311	0.242	0.167	0.188	0.154	0.077	0.103	0.059
	(0.224)	(0.257)	(0.18)	(0.444)	(0.463)	(0.428)	(0.373)	(0.391)	(0.361)	(0.267)	(0.305)	(0.235)
% LTV > 95%	0.018	0.021	0.014	0.191	0.222	0.169	0.11	0.127	0.099	0.037	0.055	0.023
	(0.133)	(0.145)	(0.118)	(0.393)	(0.416)	(0.375)	(0.313)	(0.333)	(0.299)	(0.188)	(0.227)	(0.151)
Median DSTI	0.251	0.266	0.231	0.252	0.268	0.239	0.221	0.227	0.215	0.209	0.219	0.2
	(1.592)	(1.219)	(1.914)	(8.339)	(0.496)	(10.858)	(1.416)	(1.473)	(1.378)	(2.052)	(1.687)	(2.281)
Turned down for credit	0.155	0.187	0.12	0.212	0.252	0.185	0.165	0.163	0.166	0.091	0.104	0.081
	(0.362)	(0.39)	(0.325)	(0.409)	(0.434)	(0.388)	(0.371)	(0.369)	(0.372)	(0.287)	(0.305)	(0.273)
Did not apply for credit	0.024	0.034	0.014	0.048	0.049	0.047	0.032	0.045	0.024	0.023	0.031	0.017
	(0.154)	(0.181)	(0.116)	(0.214)	(0.217)	(0.211)	(0.177)	(0.207)	(0.154)	(0.151)	(0.174)	(0.131)
% Missed payments	0.102	0.135	0.066	0.117	0.139	0.101	0.122	0.163	0.096	0.06	0.076	0.048
	(0.303)	(0.342)	(0.248)	(0.321)	(0.346)	(0.301)	(0.328)	(0.369)	(0.295)	(0.237)	(0.265)	(0.214)
% changed a servicer	0.56	0.569	0.551	0.607	0.619	0.598	0.647	0.619	0.664	0.582	0.533	0.617
	(0.496)	(0.495)	(0.497)	(0.489)	(0.486)	(0.49)	(0.478)	(0.486)	(0.472)	(0.493)	(0.499)	(0.486)
Average loan age (years)	5.733	5.694	5.775	1.401	1.405	1.399	2.531	2.581	2.499	3.598	3.456	3.7
	(4.27)	(3.768)	(4.751)	(0.49)	(0.491)	(0.49)	(1.409)	(1.395)	(1.417)	(2.087)	(2.098)	(2.073)
N	1,982	903	1,079	641	244	397	1,339	478	861	1,683	632	1,051

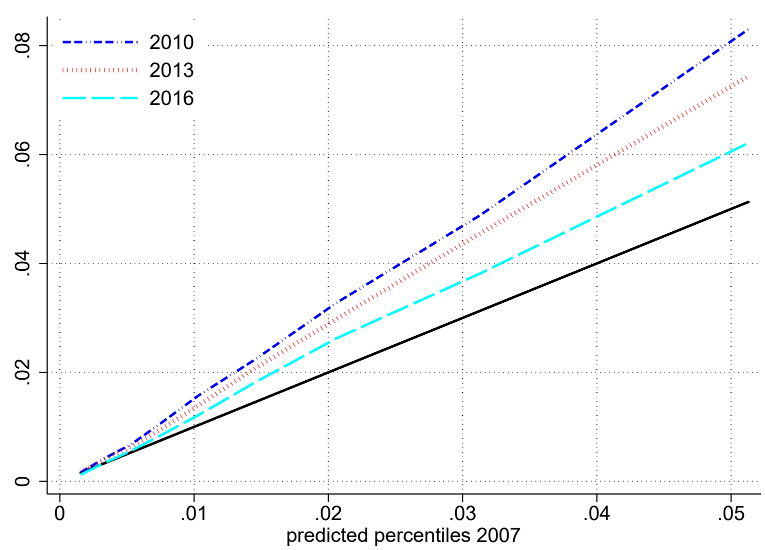
Source: Survey of Consumer Finances (SCF) 2007-2016. In the 2007 SCF we take the full sample, whereas in the subsequent waves we restrict the sample to mortgages issued or refinanced after 2008. Standard deviations are in parentheses. To account for multiple imputation, survey weights are divided by 5. Income and net worth are summed over all household members. "Turned down for credit" denotes a dummy variable that gets a value one if a respondent was turned down for credit. The variable "Did not apply for credit" is a dummy variable that gets value one if a respondent did not apply for credit for the fear of being rejected. Missed payments reflects if respondent is currently behind payments on the 1st or 2nd mortgage.
Acronyms: LTV: the loan-to-value, DSTI: debt service to income.

Table 9: Percentile Values of Predicted Foreclosure Probability Distribution: Mortgages Issued or Refinanced after 2008

Survey year:	2010			2013			2016		
Lender:	All (1)	Non-banks (2)	Banks (3)	All (4)	Non-banks (5)	Banks (6)	All (7)	Non-banks (8)	Banks (9)
Mean	0.035	0.043	0.029	0.029	0.031	0.028	0.026	0.029	0.024
p(25)	0.007	0.010	0.006	0.007	0.007	0.006	0.006	0.006	0.005
p(50)	0.017	0.021	0.015	0.016	0.018	0.014	0.014	0.016	0.014
p(75)	0.044	0.048	0.038	0.037	0.043	0.034	0.033	0.035	0.030
p(95)	0.125	0.170	0.105	0.107	0.112	0.105	0.090	0.101	0.080
N	641	244	397	1,339	478	861	1,683	632	1,051

Notes: This table reports selected percentile values of foreclosure probability distribution in years 2010, 2013 and 2016. We estimate the foreclosure model using the full-sample of the 2007-2009 SCF, but for years 2010, 2013 and 2016 here we report predicted probabilities for mortgages issued or refinanced after 2008. In each survey year we report unconditional percentile values (columns (1), (4), (7), (10)), whereas the rest of the columns report percentile values conditional on lender type i.e. banks and non-banks.

Figure 6: Predicted Percentiles: with the Lender Indicator



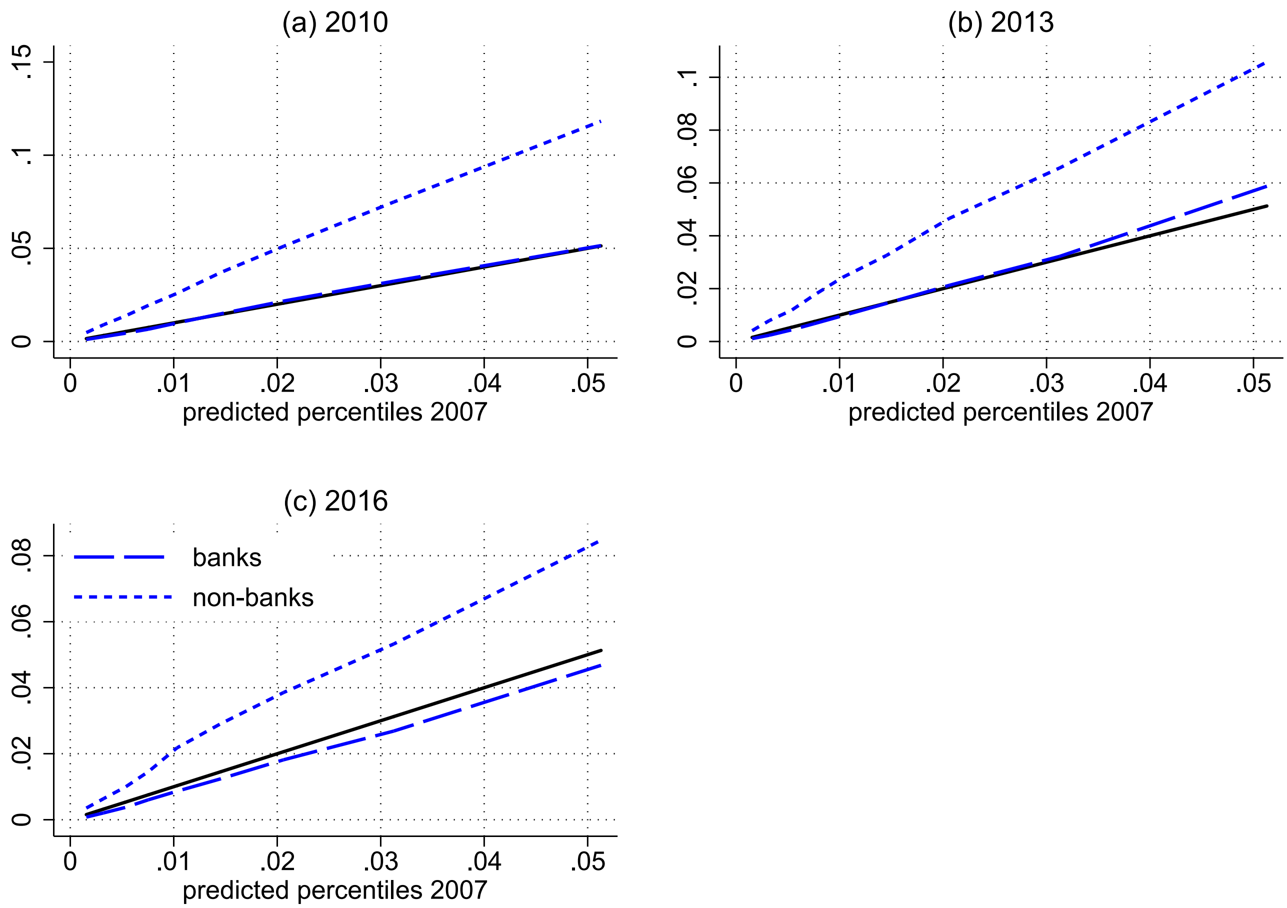
Notes: This figure plots percentiles of predicted foreclosure probabilities in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, column (1)). The percentiles are computed using 10 equidistant points and survey analysis weights.

Table 10: Foreclosure Model Estimation: with the Lender Indicator

Dependent variable:	Foreclosure in 2007-2009			
Estimation method:	Probit		Logit	
	(1)	(2)	(3)	(4)
Non-bank lender	0.203 (0.184)	0.259 (0.184)	0.395 (0.451)	0.550 (0.466)
Age	0.104 (0.109)	0.096 (0.098)	0.240 (0.267)	0.214 (0.246)
Age-squared	-0.107 (0.115)	-0.102 (0.106)	-0.241 (0.287)	-0.222 (0.270)
African-American	0.358** (0.181)	0.387** (0.185)	0.818** (0.406)	0.890** (0.419)
Hispanic	0.369 (0.310)	0.406 (0.269)	0.880 (0.725)	0.954 (0.630)
Married	-0.244* (0.146)	-0.232* (0.137)	-0.477 (0.327)	-0.470 (0.310)
Some college/college degree	0.075 (0.182)	0.099 (0.174)	0.289 (0.450)	0.336 (0.437)
Unemployed in the last yr	0.336* (0.176)	0.319* (0.164)	0.713* (0.405)	0.687* (0.387)
DSTI ratio	0.035 (0.084)	0.033 (0.037)	0.076 (0.183)	0.064 (0.086)
Has other residential RE	0.542*** (0.171)	0.563*** (0.164)	1.122*** (0.403)	1.180*** (0.383)
Adjustable rate mortgage	0.269 (0.236)	0.340* (0.203)	0.578 (0.565)	0.748 (0.475)
FHA/VA	0.200 (0.212)	0.220 (0.213)	0.488 (0.485)	0.544 (0.498)
Has 2nd/3rd mortgage	-0.235 (0.523)	-0.198 (0.519)	-0.607 (1.494)	-0.491 (1.539)
Has refinanced	-0.150 (0.147)	-0.182 (0.148)	-0.326 (0.342)	-0.412 (0.347)
Missed payments	0.528 (0.620)	0.524 (0.414)	0.944 (1.650)	0.936 (0.893)
Turned down for credit	0.003 (0.202)	0.028 (0.200)	0.024 (0.468)	0.073 (0.466)
Net worth	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Mortgage age	-0.010 (0.067)	-0.027 (0.065)	-0.028 (0.161)	-0.068 (0.160)
Mortgage age-squared	0.001 (0.004)	0.002 (0.004)	0.004 (0.010)	0.004 (0.011)
Log house value	-0.034 (0.106)	-0.059 (0.089)	-0.093 (0.243)	-0.157 (0.208)
LTV	1.018** (0.425)		2.525** (0.984)	
$0.25 \leq$ LTV < 0.5		0.162 (0.297)		0.377 (0.744)
$0.5 \leq$ LTV < 0.75		0.317 (0.267)		0.722 (0.655)
LTV ≥ 0.75		0.412 (0.298)		0.937 (0.740)
Pseudo R^2	0.201	0.176	0.198	0.171
N	1,982	1,982	1,982	1,982

Source: Survey of Consumer Finances 2007-2009 panel.
STATA program *scfcombo* from Pence (2015) is used to account for imputation uncertainty and compute bootstrapped standard errors. Number of bootstraps is set equal to 200. Standard errors are reported in parentheses.
Acronyms: LTV: the loan-to-value, DSTI: debt service to income.

Figure 7: Predicted Percentiles by Lender Type: with the Lender Indicator



Notes: This figure plots percentiles of predicted foreclosure probabilities, conditional on lender type, in 2010, 2013 and 2016 against percentiles of predicted foreclosure probabilities in 2007. The black solid line is a 45° line. The percentile values are computed based on the estimates from the probit model on the SCF data (Table 2, column (1)). The percentiles are computed using 10 equidistant points and survey analysis weights.

Table 11: Percentile Values of Predicted Foreclosure Probability Distribution: with the Lender Indicator

Survey year:	2007			2010			2013			2016		
Lender:	All (1)	Non-banks (2)	Banks (3)	All (4)	Non-banks (5)	Banks (6)	All (7)	Non-banks (8)	Banks (9)	All (10)	Non-banks (11)	Banks (12)
Mean	0.022	0.029	0.013	0.033	0.048	0.022	0.031	0.043	0.023	0.025	0.035	0.019
p(25)	0.004	0.008	0.002	0.006	0.011	0.004	0.005	0.010	0.003	0.004	0.008	0.003
p(50)	0.010	0.016	0.006	0.016	0.026	0.010	0.014	0.024	0.010	0.012	0.022	0.009
p(75)	0.025	0.034	0.015	0.039	0.061	0.026	0.036	0.055	0.026	0.031	0.045	0.023
p(95)	0.075	0.101	0.050	0.123	0.171	0.080	0.118	0.145	0.088	0.092	0.121	0.067
N	1,982	904	1,078	2,886	1,757	1,900	2,509	880	1,629	2,590	946	1,644

Notes: This table reports selected percentile values of foreclosure probability distribution in base year 2007 and in years 2010, 2013 and 2016. In each survey year we report unconditional percentile values (columns (1), (4), (7), (10)), whereas the rest of the columns report percentile values conditional on lender type i.e. banks and non-banks.