DISCUSSION PAPER SERIES

No. 10476

FORCED ASSET SALES AND THE CONCENTRATION OF OUTSTANDING DEBT: EVIDENCE FROM THE MORTGAGE MARKET

Giovanni Favara and Mariassunta Giannetti

FINANCIAL ECONOMICS

Centre for Economic Policy Research

ISSN 0265-8003

FORCED ASSET SALES AND THE CONCENTRATION OF OUTSTANDING DEBT: EVIDENCE FROM THE MORTGAGE MARKET

Giovanni Favara and Mariassunta Giannetti

Discussion Paper No. 10476
March 2015
Submitted 27 February 2015

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801
www.cepr.org

FORCED ASSET SALES AND THE CONCENTRATION OF OUTSTANDING DEBT: EVIDENCE FROM THE MORTGAGE MARKET[†]

Abstract

We provide evidence that lenders differ in their ex post incentives to internalize price-default externalities associated with the liquidation of collateralized debt. Using the mortgage market as a laboratory, we conjecture that lenders with a large share of outstanding mortgages on their balance sheets internalize the negative spillovers associated with the liquidation of defaulting mortgages and are thus less inclined to foreclose. We find that zip codes with higher concentration of outstanding mortgages experience fewer foreclosures, more renegotiations of delinquent mortgages, and smaller house prices declines. These results are not driven by prior local economic conditions, mortgage securitization or unobservable lender characteristics.

JEL Classification: G01, G21, R31 and R38
Keywords: bank concentration, fire sales, foreclosures and house prices

Giovanni Favara giovanni.favara@frb.gov
Federal Reserve Board

Mariassunta Giannetti mariassunta.giannetti@hhs.se
Stockholm School of Economics, ECGI and CEPR

[†] We thank Manuel Adelino, Gene Amromin, Elliot Anenberg, Eric Engstrom, Paul Kalem, Anastasia Kartasheva, Benjamin Keys, Tim Landvoigt, Elena Loutskina, Steven Ongena, Karen Pence, Anthony Pennington-Cross, Amit Seru, Steve Sharpe, Shane Sherlund, Greg Udell, Vikrant Vig, and seminar partici- pants at the NBER Financing Housing Capital Conference, the New York University Stern School of Business, the University of British Columbia Sauder School of Business, the Federal Reserve Bank of Chicago, the Board of Governors of the Federal Reserve System, Boston University, Georgia State University, University of California, Irvine, the University of Lausanne and EPFL, the University of Amsterdam, the Goethe University in Frankfurt, the EFA in Lugano, the FIRS Conference in Quebec City, the SED Conference in Seoul, the Summer Meeting of the Econometric Society at the University of Southern California. We also thank Mihir Gandhi for oustanding research assistance. Giannetti acknowledges financial support from the Jan Wallander and Tom Hedelius Foundation and the Bank of Sweden Tercentenary Foundation. This paper represents the views of the authors and not those of the Federal Reserve System or its Board of Governors.

The notion that forced asset sales may fetch prices below their fundamental values is central in financial economics (Shleifer and Vishny, 1992), and is supported by a large body of empirical research (Pulvino, 1998; Coval and Stafford, 2007; Bemmelech and Bergman, 2008). Price dislocations associated with forced asset sales may generate externalities that feedback on asset values and cause price-default spirals, especially in illiquid markets with collateralized lending (Kiyotaki and Moore, 1997; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). If asset liquidations in these markets may trigger downward spirals in asset prices and impair the balance sheets of other market participants, an important question is why lenders do not take actions to avoid collateral liquidation (Shleifer and Vishny, 2011). Surprisingly, the theoretical and empirical literature on this question is scant.

The purpose of this paper is to provide evidence that lenders differ in their ex post incentives to internalize price-default externalities, and that this heterogeneity depends on the share of collateralized debt in their portfolios. Our conjecture is that lenders that hold a large proportion of the outstanding collateralized debt internalize the feedback effects of liquidation decisions on collateral values and may be more inclined to renegotiate to avoid price-default spirals. Using data on foreclosures and house prices during the 2007-2010 U.S. housing crisis, we find evidence that such incentives are at work and are economically significant.

The recent real estate crisis is an ideal laboratory for testing our conjecture for three reasons. First, mortgages, the standard debt contract in the housing market, entitle lenders to seize a house and sell it through a foreclosure process if a borrower defaults. Second, given the illiquidity of the housing market, foreclosures are likely to generate price discounts that may spillover to non-distressed neighboring houses (Campbell, Giglio and Pathak, 2011; Harding, Rosenblatt, and Yao, 2009; Anenberg and Kung, 2013; Hartley, 2014). Third, the recent crisis has seen an unprecedented increase in foreclosures and decline in house prices, with feedback loops between foreclosures and prices contributing to the severity of the crisis. For instance, it has been shown that foreclosures led to a generalized decline in house prices (Mian, Sufi and Trebbi, 2015), which in turn caused additional foreclosures, as borrowers moved into negative equity positions (Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010), triggering further price declines (Guren and McQuade, 2013).

We begin the analysis with a stylized model of the housing market in which negative income shocks force distressed homeowners to default on their debt obligations, and foreclosures trigger a decline in house prices, as debt liquidation creates an imbalance of housing demand and supply. In our simple setting, the initial decline in house prices is amplified as non-distressed homeowners that move into negative equity positions find it optimal to default. When mortgages are held by many (atomistic) lenders, each lender places little weight

on the effects of its foreclosure decisions on local house prices, and thus defaults are followed by further defaults. In contrast, when lenders hold a large share of outstanding mortgages on their balance sheets they internalize the adverse effects of their liquidation decisions on house prices, and have stronger incentives to renegotiate defaulting loans. Fewer liquidations mitigate the adverse impact of the initial decline in house prices, leading to fewer defaults.[1]

To test this theoretical prediction, we focus on the 2007-2010 U.S. housing crisis and perform two sets of tests. First, we use zip code level data on foreclosures, house prices and concentration of outstanding mortgages. Zip codes are the finest geographical areas for which we are able to measure the concentration of outstanding mortgages on lenders' balance sheets, and arguably the largest areas within which foreclosures are likely to generate negative externalities on house prices.[2] Second, for a subset of lenders with available data on mortgage performance, we use loan level data to test whether the same lender's incentives to foreclose on defaulting mortgages depend on the proportion of the zip code's outstanding mortgages on its balance sheet.

In the zip code level analysis, we construct an index of local concentration of mortgages on lenders' balance sheets using data on mortgages retained by the four biggest holders in a zip code. Lenders with a large share of retained mortgages in a zip code are expected to avoid foreclosures in order to minimize losses due to foreclosure externalities. We find empirical support for this conjecture. An increase in the index of outstanding mortgage concentration from the bottom to the top decile of the distribution reduces, all else equal, the foreclosure rate by over 40 percent in an average zip code. We obtain these results controlling for a large set of zip code characteristics, proxies for borrower. creditworthiness, and standard controls for local housing, income, and demographic characteristics. Furthermore, these results are obtained after controlling for unobserved factors that uniformly affect zip codes within a county, such as income shocks, local market conditions and ex ante lender competition

A causal interpretation of these results relies on the assumption that the share of loans retained on a lender's balance sheet is orthogonal to the credit quality of mortgages originated. However, there might be selection effects with safer loans retained and riskier loans securitized. In addition, lenders' decision to keep mortgages on their balance sheets may be jointly determined by unobservable lender and local market characteristics. We address these concerns in two steps. First, we control for the fraction of loans that are 90 or more

[1] Although the foreclosure externality in this setting works through the borrowers' incentives to strategically default, other mechanisms may lead lenders to internalize the consequences of their foreclosures decisions. Negative spillovers could, for example, arise if the negative equity positions of borrowers constrain their ability to refinance their mortgages or if the fall in prices impair the balance sheet of lenders, for instance through the holdings of previously repossessed properties.

[2] See Mian, Sufi and Trebbi (2015) for empirical evidence on foreclosure externalities at the zip code level.

days delinquent throughout the analysis. Mortgage delinquency is the single most important predictor of foreclosures and is likely to absorb most of the differences in ex ante loan quality across zip codes. Second, we provide evidence consistent with a casual mechanism running from the concentration of outstanding mortgages to foreclosure rates by exploiting the cross-sectional implications of our hypothesis.

For instance, we find that the concentration of outstanding mortgages reduces foreclosure rates to a larger extent in zip codes with higher delinquency rates, reassuring that our findings are not driven by ex ante differences in the quality of borrowers. We also study how the results vary across jurisdictions with different foreclosure procedures. We expect that any lender, regardless of its outstanding mortgages in the neighborhood, has weaker incentives to foreclose in states with costly foreclosure procedures. Consistent with this idea, we find that the concentration of outstanding mortgages is associated with fewer foreclosures in non-judicial states where foreclosure costs are lower. We are also able to show that in zip codes with higher concentration of outstanding mortgages more delinquent mortgages are renegotiated. These results strengthen the interpretation that lenders with a large fraction of the outstanding mortgages differ in their ex post incentives to resolve distress and not in their ex ante ability to screen borrowers.

We next explore the role of securitization. While securitization increases the dispersion of outstanding mortgages strengthening lenders' incentives to foreclose, securitization may also lead to renegotiation frictions for reasons that are orthogonal to the one we propose. For instance, dispersed ownership brought about by securitization, or agency problems between servicers of securitized loans and investors may impede mortgage renegotiation (Piskorski, Seru and Vig, 2010; Agarwal et al., 2011). To separate the role played by securitization, all our specifications control for the share of loans securitized in each zip code, and the share of mortgages securitized with GSEs. In some specifications, we also decompose the index of concentration of outstanding mortgages to separate the fraction of loans retained by the four biggest holders in a zip code from the fraction of loans securitized in the same zip code. The outcomes of these tests reassure us that the effects of outstanding mortgage concentration are distinct from those related to securitization.

We then address the concern that our findings are driven by lenders' unobserved characteristics, such as organizational structures and renegotiation capabilities. For example, lenders' ability to collect soft information on borrowers' quality may affect their ex ante incentive to hold mortgages on their balance sheets, and their ex post incentives to renegotiate defaulting mortgages. We find that standard proxies of soft information, such as lenders' size and the geographical diversification of their portfolios, do not explain why zip codes with higher concentration of outstanding mortgages experience fewer foreclosures. To further ad-

dress the concern that lenders' unobserved characteristics may be driving our findings, we also use loan level data and perform within-lender test to evaluate whether the propensity of the same lender to foreclose on a defaulting mortgage varies with the share of mortgages that the lender has retained on its balance sheet in a zip code. Consistent with our zip code level evidence, we find that lenders are less willing to foreclose on delinquent loans in areas where they retained a higher fraction of outstanding mortgages. Conversely, the share of loans that lenders hold on their balance sheets is not statistically related to the foreclosure probability of securitized delinquent mortgages.

In a final step, we explore whether areas with higher concentration of outstanding mortgages also experience lower house price declines. If foreclosures adversely affect local house prices, house prices changes should be positively correlated with the concentration of outstanding mortgages in a zip code. We find that a move in the concentration index from the bottom to the top decile of the distribution leads to 22 percent lower rate of house price declines in the average zip code.

Our paper is most closely related to empirical research on fire sales of real assets (Shleifer and Vishny, 2011). This literature focuses on the negative externalities associated with asset sales in economic downturns. For example, Benmelech and Bergam (2011) document that during recessions, a firm's bankruptcy reduces collateral values of other industry participants imposing negative externalities on their non-bankrupt competitors. Asquith, Gertner, and Scharfstein (1994) find that lenders avoid liquidation and prefer to renegotiate troubled loans when industry conditions deteriorate. We depart from this literature by studying how lenders' incentives to avoid fire sale externalities depend on lenders' market structure. To our knowledge, this is the first paper to explore the role of market structure on lenders' liquidation incentives and asset prices.

As our analysis focuses on the housing market, our paper also contributes to the literature on the recent housing crisis. A number of papers explore how differences in the local mortgage markets are associated with the intensity of the crisis (e.g., Mian and Sufi, 2009 and 2011; Mayer, Pence and Sherlund, 2009; Keys, et al., 2010; Purnanandam, 2011) and whether securitization has exacerbated the intensity of the crisis by inhibiting the renegotiation of delinquent loans (Agarwal, et al., 2011; Piskorski, Seru and Vig, 2010; Adelino, Gerardi and Willen, 2013). Our paper focuses, instead, on the incentives of lenders to foreclose portfolio loans, relates such incentives to the share of outstanding mortgages they retained in a neighborhood, and studies the implications for foreclosure rates and house prices.

A related strand of literature studies the costs and benefits of ex post loan renegotiations. While renegotiations may prevent foreclosures and limit deadweight losses for borrowers and lenders, such policies may strengthen borrowers' incentives to default strategically (Agarwal

et al., 2014; Mayer at al., 2014). Our stylized model suggests that loan renegotiations limit the losses of a lender with a large share of outstanding mortgages even in presence of strategic defaults.

The paper is also related to the literature that explores the effects of banks' loan concentration on bank-firm relationships (Berger, Miller, Petersen, Rajan, and Stein, 2005), the loan supply (Garmaise and Moskowitz, 2006), and the transmission of monetary policy changes to mortgage rates (Scharfstein and Sunderam, 2013). All these papers study the effects of market power concentration on loan origination and contract terms. We focus, instead, on the role of concentration of outstanding mortgages on lenders' ex post incentives. By showing that a market with dispersed lenders is more prone to fire sales externalities, we also provide an alternative interpretation to the view that competition in the credit market erodes financial stability because it distorts lenders' risk taking decisions by lowering their profit margins (Keely, 1990).

The rest of the paper is organized as follows. Section 1 describes the theoretical model and summarizes the theoretical predictions on the relationship between the concentration of outstanding mortgages on lenders' balance sheets, foreclosures and house prices. Section 2 describes the data and our empirical strategy. Section 3 presents our main empirical results on foreclosure rates and Section 4 on house prices. Section 5 concludes.

1 Theory and Testable Implications

In this section, we develop a simple model to illustrate the relationship between foreclosures, house prices and the concentration of outstanding mortgages. In the model, foreclosures generate an imbalance of housing supply and demand, and cause a decline in the equilibrium prices. As prices decline, borrowers that would otherwise have been able to repay their mortgages default strategically, because the value of their homes falls below the value of their mortgages. In this setting, we show that lenders holding a large share of the outstanding mortgages internalize the negative spillovers of foreclosures associated with generalized defaults, and are thus more inclined to avoid foreclosures. In the following sections, we bring this intuitive prediction to the data.

1.1 The model

1.1.1 Assumptions

There are two dates and two groups of agents of mass 1, households (indexed by i) and lenders. At $t = 0$, some households enter the period with one unit of housing endowment

$h_{0i} = 1$, and an outstanding mortgage payment B. At $t = 1$, households enjoy utility from consumption, $c_i \geq 0$, and housing $h_i \in \{0, 1\}$:

$$U_i = c_i + \gamma_i h_i,$$

where γ_i is uniformly distributed, $\gamma_i \sim \mathcal{U}\ [0, \overline{\gamma}]$, and captures heterogeneity in utility from home ownership. Households with endowment $h_{0i} = 1$ have the highest utility from housing services. Aggregate housing supply is fixed at $\overline{H} < \overline{\gamma}$.

At $t = 1$, households receive a random income w_i, which is independently distributed from γ_i. With probability q, everyone receives w. With probability $1 - q$, a fraction e of households suffer a negative income shock and receives θw, with $0 < \theta < 1$. We assume that income shocks are observable even though not verifiable. We also assume that distressed households are unable to repay B:

$$w > B > \theta w, \tag{1}$$

and that lenders may partially recover B by selling the houses of these households at a price p (to be derived below).

Under these assumptions, household i's budget constraint at $t = 1$ depends on the realization of the income shock, the repayment or default on the mortgage debt, and whether the lender forecloses in case of default:

$$w_i = \begin{cases} c_i + B + p(h_{1i} - h_{0i}) & \text{no default} \\ c_i + p h_{1i} & \text{default \& foreclosure} \end{cases}.$$

1.1.2 Equilibrium housing prices and strategic defaults

In absence of shocks, the unit housing demand is pinned down by the following condition:

$$\gamma_i \geq p,$$

which relates the utility value of owning to the price of housing. Since γ_i is uniformly distributed, the equilibrium price is determined by equating aggregate demand and supply:

$$p = \overline{\gamma} - \overline{H} > B.$$

At this price, all households repay B and, under our assumption on the initial distribution of housing, they hold on to their houses.[3]

[3] If the repayment obligation were larger than the equilibrium price, $B > p$, households would default as they have the option to surrender their houses to the lender. The condition, $\overline{\gamma} - \overline{H} > B$, rules out this

In contrast, when some households are hit by a negative income shock, they cannot afford to repay B (by (1)). If lenders foreclose on these distressed households, a fraction e of them is excluded from the housing market. The market clearing condition becomes:

$$(1-e)(\overline{\gamma}-p)=\overline{H},$$

and the equilibrium price is:

$$p^L=\overline{\gamma}-\frac{\overline{H}}{1-e}.$$

It follows immediately that p^L is strictly lower than p, because a fraction e of households with high utility from owning cannot participate in the market, reducing aggregate demand.

An equilibrium in which lenders foreclose on distressed households implies that $p^L < B$, otherwise distressed households would prefer to sell their houses and pay back their mortgage payment. This equilibrium also implies that non distressed households always default strategically because they can purchase a house at a price lower than B, even though they can afford to repay B.[4] Therefore, in equilibrium, it must be that:

$$\theta w<\overline{\gamma}-\frac{\overline{H}}{1-e}\leqslant w,$$

meaning that households that suffer a negative income shock are unable to participate in the housing market (the first inequality), while non distressed households default strategically.[5] The above discussion can be summarized in the following Lemma.

Lemma *If lenders foreclose on distressed households, house prices fall and non distressed borrowers find it optimal to default strategically.*

It is important to note that in this setting atomistic lenders always find it optimal to foreclose because the highest payment a distressed borrower can promise is θw, but the equilibrium price that prevails under foreclosure is $p^L > \theta w$.

possibility.

[4] The same result would be obtained if other investors purchased the houses and provided housing services to households that have strategically defaulted.

[5] This is the only equilibrium with foreclosure and strategic defaults. The condition $p^L=\overline{\gamma}-\frac{\overline{H}}{1-e}<w$ is implied by $p^L<B<w$. An equilibrium in which $p^L>w$ does not exist because no households would be able to purchase a house, causing the house price to fall. Similarly, it cannot be that $p^L<\theta w$. If this were the case, at least as many households as in the state of the world in which no income shock occurs would would be able to purchase a house, driving the equilibrium house price above θw.

1.1.3 Lenders' shares of outstanding mortgages and foreclosure decisions

We now consider the case in which one lender holds a large share, ξ, of the outstanding mortgages in the market (ξ-lender), and the remaining share $(1-\xi)$ is dispersed among many atomistic lenders.[6]

If the ξ-lender were to renegotiate the mortgage payment of distressed households, while the other atomistic lenders foreclosed on defaulting borrowers, the aggregate housing demand would be:

$$(1-\xi)(1-e)(\overline{\gamma}-p^{L'})+\xi(\overline{\gamma}-p^{L'}),$$

and the equilibrium price

$$p^{L'}=\overline{\gamma}-\frac{\overline{H}}{(1-\xi)(1-e)+\xi},$$

which is strictly larger than p^L, and increasing in ξ. For values of ξ close to 1, the equilibrium price could be such that $p^{L'}\geq B$, and no default (strategic and non-strategic) would take place. For lower values of ξ, the equilibrium house price may fall below B and any borrowers, including non distressed ones, find it optimal to default.

Under the assumption that income shocks are observable, the $\xi-$lender can offer to reduce the mortgage payment of non distressed households to $B'=p^{L'}<B$, and these households would find it optimal to accept the offer.[7] In this case, the $\xi-$lender is willing to renegotiate with, rather than foreclose on, distressed households if

$$(1-e)p^{L'}+e\theta w>p^L, \tag{2}$$

where the left hand side of (2) is the total return from renegotiation. Using the equilibrium prices $p^{L'}$ and p^L, this condition can be rewritten as

$$\frac{\xi}{(1-\xi)(1-e)+\xi}\frac{\overline{H}}{1-e}>\overline{\gamma}-\frac{\overline{H}}{(1-\xi)(1-e)+\xi}-\theta w_1$$

which is more likely to hold as ξ increases.

Also, if this condition holds, not only there are fewer foreclosures and smaller house price declines, but aggregate mortgage losses are also lower. The reason is that all lenders obtain a higher average repayment, including dispersed lenders who are able to foreclose houses at

[6] The trust of the results we present hereafter continues to hold if we allow for several ξ-lenders and mixed strategies over foreclosure and renegotiation decisions.

[7] The assumption that at least the lender with a high share of outstanding mortgages can distinguish households that suffer a negative income shock is crucial (see Ghent (2011) for some supporting evidence). If this was not possible, intact households could strategically ask for a loan modification. The model can, however, be modified to allow banks to imperfectly distinguish between intact and distressed households.

a higher equilibrium price.[8]

The following proposition summarizes this discussion

Proposition *There are fewer foreclosures and smaller declines in house prices in areas where lenders hold a large share of the outstanding mortgages.*

1.1.4 Discussion

In this stylized model, foreclosures trigger more defaults and exacerbate house price declines because foreclosures generate an externality that operates through the incentives of non distressed borrowers to default strategically. Although the notion that a generalized fall in house prices may lead to strategic defaults is supported by empirical evidence (Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010; Guiso, Sapienza and Zingales, 2013), the concentration of outstanding mortgages could mitigate the adverse effects of foreclosures even if the externality operated through different mechanisms. For instance, a given income shock may be amplified if foreclosures lead to price declines that deteriorate the balance sheets of all households and cause a reduction in real activity, which in turn may lead to further defaults. Also, foreclosures and price declines may impair the balance sheets of lenders if lenders have direct exposures to local real estate through, for instance, the holdings of previously repossessed properties. Alternatively, externalities may arise because foreclosures reduce the amenity value of neighboring houses (Fisher, Lambie-Hanson, and Willen, 2014). In all these cases, we would expect that lenders with a large shares of outstanding mortgages have stronger incentives to avoid foreclosures. Our empirical analysis aims to capture any of these mechanisms.

2 Empirical Challenges

The main testable hypothesis of our analysis is that lenders that retain a large share of the outstanding mortgages on their balance sheets are more likely to internalize the adverse effects of foreclosures and reduce their propensity to foreclose.

To assess the validity of this hypothesis, we use data on local housing markets. We start by computing the share of mortgages outstanding in a neighborhood that are on a lender's balance sheet. This requires information on the identity of the lender originating mortgages in a given neighborhood, and information on whether these mortgages are retained

[8] When a lender renegotiates a defaulting loan, other lenders have stronger incentives to foreclose because the equilibrium house price is higher. Thus, a lender with a large share of outstanding mortgages cannot prevent strategic defaults, but it can mitigate the effects of negative income shocks on foreclosures and house prices. These mitigating effects would be larger if defaults were costly for borrowers.

or securitized. This information can only be obtained from the Home Mortgage Disclosure Act (HMDA) data, the largest source of primary U.S. mortgage originations, covering over 90 percent of the mortgage activity of commercial banks, thrifts, credit unions, and mortgage companies (see, e.g., Mian and Sufi, 2009; Loutskina and Strahan, 2011, Favara and Imbs, 2014). From HMDA we use data on lender's identity, location of the property purchased with a mortgage, and mortgage disposition to compute zip code level measures of outstanding mortgage concentration.[9]

Unfortunately, HMDA does not provide information on loan performance, including defaults and foreclosures. Since this information is crucial for our analysis, we obtain foreclosure data from RealtyTrac.com, a leading online marketplace for foreclosure properties, covering over 92 percent of the housing units in the U.S. RealtyTrac data, however, cannot be matched with mortgage originations in HMDA, preventing us to test our main hypothesis with loan level data. RealtyTrac information on the location of the foreclosed properties is thus used to compute the number of foreclosures in a given zip code, which enables us to conduct most of our analysis with zip code level data. Section 2.1 provides precise details on variables' construction.

To ascertain that lenders' propensity to foreclose on defaulting mortgages does not depend on unobservable lenders' characteristics (such as organizational structures and renegotiation capabilities), we also perform a loan level analysis by merging HMDA information on mortgage originations with information on mortgage performance from the Lender Processing Services (LPS) Applied Analytics. LPS covers roughly 60 percent of the mortgage market in the United States and contains information on mortgage defaults and foreclosure starts.

The merged HMDA-LPS data enable us to test whether the same lender has a stronger propensity to foreclose on mortgages in zip codes in which it has retained a smaller share of outstanding mortgages. While useful, this loan level analysis has important drawbacks, due to some features of LPS data. First, LPS collects data from the largest mortgage servicers, which usually service mortgages securitized in the private market or through government agencies. Since only a small fraction of portfolio loans are serviced by third-party services, the coverage of portfolio loans in LPS is limited. In addition, LPS records accurately when foreclosures start, but not when they are completed. However, a delinquent borrower may become current without the property's eviction and sale for several reasons, including a loan modification. Therefore, the HMDA-LPS data may record too many foreclosures, and even count renegotiations as foreclosures. Finally, LPS reports only mortgage serviced by third-party servicers. Since the incentives of originators and servicers of portfolio loans may be

[9] Since HMDA reports census tract information of the property location, we match census tracts to zip codes using the crosswalk provided by the U.S. Department of Housing and Urban Development.

imperfectly aligned, originators may find it difficult to renegotiate defaulting loans and may appear more inclined to foreclose. All these limitations stack the deck against finding any relationship between the share of a neighborhood's mortgages on a lender's balance sheet and the lender's propensity to foreclose in that neighborhood.

2.1 Main variables and descriptive statistics

In the zip code level analysis, our sample consists of 6,503 zip codes in 696 urban counties. We focus on urban areas because house price dynamics, borrower characteristics, and mortgage lending decisions have different determinants in rural, often poor, areas. In addition, it is well known that HMDA coverage is limited and not representative in rural areas (Avery, Brevoort, Canner, 2007).

To measure the local concentration of outstanding mortgages on lenders' balance sheets, we construct an index, called $Top4$, which is computed from HMDA as the number of mortgages retained by the four biggest holders in a zip code between 2004 and 2006, divided by the total number of mortgages originated in that zip code during the same period:

$$Top4_{z,04-06} \equiv \frac{MR_{1,z} + MR_{2,z} + MR_{3,z} + MR_{4,z}}{TotalOriginations_z}. \tag{3}$$

In equation (3), $MR_{i,z}$ is the number of mortgages retained by the lender ranked i in zip code z over the 2004-2006 period and $TotalOriginations_z$ is the total number of loans originated in zip code z by all lenders over the same period.[10] The numerator of the $Top4$ index uses mortgages retained because we want to measure the credit risk exposure of lenders to the local market. In our analysis, a mortgage is classified as retained, if it is not sold within a year to a GSE or a non-affiliated institution. Since the process of securitization takes on average two to three months, we consider only mortgages originated in the first three quarters of the year, as mortgages issued at the end of the year may be securitized at the beginning of the following year and thus improperly classified as retained.[11] The $Top4$ index is computed over the three-year interval, 2004-2006, because we want to measure concentration of mortgage holdings in terms of the stock of retained mortgages just before the U.S. foreclosure crisis.[12] As shown in Figure 1, there is substantial variation in the concentration of outstanding mortgages. In some zip codes, the top 4 holders retain less than 5 percent of the outstanding

[10] Results are similar to the ones we present if we use the volume rather than the number of mortgages.

[11] The coefficient of correlation between the same index of concentration computed with and without the mortgages originated in the last quarter of each year is approximately 0.9.

[12] We consider only mortgages originated for the purchase of single-family, owner-occupied houses, because common house price indexes, including Corelogic, which we use to study the house price implications of lenders' incentives to foreclose, consider only this type of properties. We also exclude loans for refinancing and home improvement.

loans, in others over 30 percent. Summary statistics for this index are reported in Table 1.

By construction, the proportion of securitized mortgages in each zip code is negatively correlated with the concentration of mortgages held on lenders' balance sheets. To isolate variation in the $Top4$ index due to securitization, we decompose the index as follows:

$$Top4_{z,04-06} = Top4\_ret_{z,04-06} \times (1 - \sec_{z,04-06}),$$

where

$$Top4\_ret_{z,04-06} \equiv \frac{MR_{1,z} + MR_{2,z} + MR_{3,z} + MR_{4,z}}{Loans\,\mathrm{Re}\,tained_z}$$

captures variation in $Top4$ due to the share of loans retained by the four biggest holders in a zip code, and

$$\sec_{z,04-06} = \frac{Loans\,Securitized_z}{TotalOriginations_z}$$

measures the share of loans securitized in the same zip code. As shown in Figure 2, the nation-wide distribution of $Top4\_ret$ is less skewed than $Top4$, but equally dispersed across zip codes.

Table 1 also reports definitions, data sources, and summary statistics for the main outcome and control variables used in the analysis. Outcome variables are computed between 2007 and 2010 to measure zip code performance during the U.S. housing crisis.[13] In contrast, most controls are measured during the period preceding the crisis, i.e. 2004-2006.

The main outcome variable is the foreclosure rate, which is measured using RealtyTrac.com's records on properties that receive a notice of sale.[14] We standardize the number of foreclosures by either the number of single family owner occupied housing units or the number of outstanding mortgages that are 90 days or more delinquent.[15] As shown in Table

[13] Our results are invariant if we consider only the period between 2007 and 2009. We include 2010 because foreclosure completions may have been delayed until 2010 in jurisdictions that require the use of a judge to complete a foreclosure procedure (Mian, Sufi and Trebbi, 2014). The fact that our results are robust to the exclusion of 2010 suggests that the Home Affordable Modification Program (HAMP), introduced at the end of 2009 to help financially struggling homeowners avoid foreclosure by modifying loans, is unlikely to influence our results.

[14] RealtyTrac.com collects information from the moment a foreclosure procedure begins, through a notice of default, until the defaulting property is sold at a public auction through a notice of sale. We use only notice of sales to identify foreclosures, because a defaulting borrower can always reinstate loan payments after a foreclosure's start and before its completion. We also exclude real estate owned (REO) properties, i.e., properties that have been repossessed by lenders, because almost all REOs occur after a notice of sale. None of our results depends on the exclusion of REOs from the total number of foreclosures.

[15] Zip code measures of the single family housing stock come from the 2000 Census. The number of 90 plus days delinquent mortgages is from Equifax, which provides this information for a 5% representative sample of the population. We divide the number of delinquencies by 0.05 to obtain an estimate of the actual

1, there is large cross-sectional variation in the two foreclosure rates.

We also consider loan modifications to study whether lenders are more inclined to renegotiate defaulting loans in areas with a higher $Top4$ index. We compute the number of loan modifications in each zip code using LPS data and the algorithm developed by Adelino, Gerardi and Willen (2013). The algorithm identifies a loan modification whenever a mortgage is in default and there is a change in its contractual terms, such as a reduction in interest rates, a term extension or a change in the outstanding mortgage balance. For our purposes, we compute the share of portfolio and securitized loans that have been modified in a given zip code relative to all defaulting loans in the same zip code.

Another important outcome variable in our analysis is the change in house prices. If foreclosures generate negative externalities that reduce the value of nearby homes, changes in our measure of local mortgage concentration should also correlate with zip code changes in house prices. We obtain data on house prices from CoreLogic, which provides quality-adjusted house price indexes for existing single-family properties. Between 2007 and 2010, some zip codes experienced house prices depreciations of over 50 percent, others witnessed house prices changes of 2 percent or smaller.

2.2 Empirical Framework

To test our hypothesis we estimate the following cross-sectional regressions on zip code level data:

$$y_{z,07-10} = \alpha_1 Top4_{z,04-06} + 90^{+} Delinquencies_{z,07-10} + \beta X_{z,l,04-06} + \delta_{County} + \epsilon_{z,07-10},$$

where the dependent variable is the foreclosure rate, the loan modification rate, or the logarithmic change in house prices, all measured between 2007 and 2010, and $Top4_{z,04-06}$ is our measure of local concentration of mortgage holdings between 2004 and 2006.

The regression includes county fixed effects, δ_{County}, to absorb unobserved factors that uniformly affects zip codes within the same county, such as state lending or foreclosure laws, economic conditions specific to a given county and, competition in the mortgage market. The matrix of controls, $X_{z,04-06}$, summarizes observable zip code characteristics, measured between 2004 and 2006, that are likely to predict our outcome variables. This set of controls includes characteristics of the mortgage market, such as the proportion of private label and GSE securitized mortgages, and various proxies for borrower's credit quality and leverage, including the median income, the average credit score, the fraction of subprime borrowers, as well as the loan to value ratio and mortgage debt per capita in each zip code. While these

number of delinquencies in each zip code.

control variables are predetermined, none are truly exogenous. Their inclusion is an attempt to ensure that the $Top4$ index has explanatory power, correcting for the usual determinants of the outcome variables.

Importantly, our regression framework controls for the 90 days plus delinquency rate, $90^{+}Delinquencies_{z,07-10}$, in each zip code during the 2007-2010 period. The delinquency rate is the single most important determinant of foreclosures, and helps us address the main concern of our empirical analysis that the $Top4$ index may be correlated with other factors that affect foreclosures and house price dynamics. For instance, a negative correlation between the $Top4$ index and foreclosure rates could arise because lenders have retained mortgages originated to borrowers with lower probability of default. Thus, the ex ante quality of the loans, rather than differences in ex post lender's incentives to foreclose, could bias our empirical analysis.

While it is arduous to find exogenous variation in the $Top4$ index that may help disentangle these ex ante and ex post effects, we provide evidence consistent with a casual mechanism by exploiting cross-sectional differences across zip codes in the effects of $Top4$ on foreclosure rates and house prices. We introduce these additional tests after describing the main results.

3 Foreclosures and outstanding mortgage concentration

Table 2 reports our main results. In columns 1 to 3, we use foreclosures per homeowner as the dependent variable. In columns 4 to 6 we standardize the number of foreclosures with the number of mortgages that are more than 90 days delinquent. The dependent variable in the last three columns allows us to control for non-linear effects of delinquencies on foreclosures, to further minimize the concern that foreclosures rates reflect the quality of outstanding mortgages in a zip code.

A negative correlation between the $Top4$ index and foreclosure rates is consistent with the hypothesis that the local concentration of mortgage holdings mitigates the incentives to foreclose. Across all specifications estimated in Table 2, there is a statistically significant negative correlation between the $Top4$ index and foreclosure rates. Importantly, the magnitude of this negative correlation is invariant if we absorb unobserved geographical heterogeneity by including MSA fixed effects (column 1), county fixed effects (column 2), or even county subdivision fixed effects (column 3).[16] The stability of the estimated coefficients suggests that any unobservable factors correlated with neighborhood effects are unlikely to bias our

[16] County subdivisions may be important for large counties.

findings.

The economic significance of the estimated effects is sizable. In column 2, a two-standard-deviation increase in the $Top4$ index is associated with a reduction in foreclosure rate by 40 percent in the average zip code. When the number of foreclosures is standardized by the number of delinquencies, a two-standard-deviation increase in the $Top4$ index decreases the proportion of delinquent mortgages that are foreclosed by 15 percent (column 5).

3.1 Securitization and outstanding mortgage concentration

By construction, our $Top4$ index is correlated with the proportion of securitized mortgages. Securitization reduces the concentration of outstanding mortgages and thus strengthens lenders' incentives to foreclose for reasons consistent with the mechanism proposed in this paper. For instance, the lack of incentives of atomistic lenders to renegotiate defaulting loans could explain why securitized mortgages are handled by third-party servicers and why pooling and servicing agreements include restrictions that inhibit loan renegotiations (Piskorski, Seru and Vig, 2010; Agarwal et al., 2011). However, securitization may also introduces renegotiation frictions because it generates dispersed ownership of mortgage claims.[17]

Given the role played by securitization, our main specifications in Table 2 control for the fraction of mortgages securitized in each zip code. Table 3 presents the results for other specifications that help disentangle the effect of the geographic concentration of mortgages held on lenders' balance sheets from the one of securitization. In column 1, we control separately for the share of mortgages securitized between 2004 and 2006 with GSEs and non-GSEs. This breakdown is important as the two categories of securitized mortgages differ in many respects. For example, GSE mortgages are usually originated with stricter underwriting standards (Agarwal, Chang Yavas, 2012), and carry no default risk for investors of mortgage backed securities. In addition, servicers' duties and obligations in private-label-securitized mortgages differ from agency-securitized mortgages, as GSEs use reputational and financial incentives to improve servicers' performance (Levitin and Twomey, 2011). As shown, the breakdown of GSE and non-GSE securitized loans does not affect the negative correlation between $Top4$ and foreclosure rates. In column 2, we control also for the total number of mortgages originated between 2004 and 2006, and the fraction of high cost loans (i.e., mortgages originated at a spread of 3 percentage points above the rate of comparable maturity Treasury securities). These controls are meant to capture the likely deterioration in the quality of mortgages securitized during the period leading to the 2007-2010 foreclosure crisis. Once again, the effect of $Top4$ on foreclosure rates is invariant.

[17] Adelino, Gerardi and Willen (2013) provide evidence that securitization is unlikely to be the main reason why lenders are reluctant to renegotiate delinquent mortgages.

Finally, to provide additional evidence that the relationship between $Top4$ and foreclosure rates is independent from the role of securitization, we use the decomposition of the $Top4$ index described in Section 2.1, which separates the fraction of loans retained by the four biggest holders in a zip code, from the fraction of loans securitized in the same zip code:

$$Top4_{z,04-06} = Top4\_ret_{z,04-06} \times (1 - \text{sec}_{z,04-06}) \,.$$

Clearly, any effects of the $Top4\_ret$ index on foreclosure rates cannot arise from securitization or any alternative mechanisms through which securitization may affect foreclosure decisions.

The estimates in column 3 of Table 3 show that the negative effect of $Top4$ on foreclosures is uniquely driven by variation in $Top4\_ret$. The effect is not only statistically, but also economically significant: a one-standard-deviation increase in $Top4\_ret$ decreases the number of foreclosures by over 33 percent in relative terms.

3.2 Loan modifications

So far we have shown that foreclosure rates are negatively associated with the concentration of outstanding mortgages in a neighborhood. To strengthen the interpretation of our results, we also obtain data on loan modifications, and look for evidence that the lower incidence of foreclosures in zip codes with higher concentration of mortgage holdings is attained through lenders' willingness to renegotiate defaulting loans.

To measure mortgage renegotiations, we rely on the algorithm of Adelino, Gerardi and Willen (2013), which identifies a loan modification in LPS data whenever the interest rate, maturity or the outstanding balance of a mortgage change, conditional on the mortgage being delinquent. We keep track of the number of modifications of portfolio and securitized loans during the 2007-2010 period, and compute modification rates as the number of loans modified in a given zip code relative to all defaulting loans in the same zip code.

Table 4 presents the results. Column 1 uses the modification rate of portfolio loans as dependent variable, while column 2 focuses on the modification rate of securitized loans. Consistent with the interpretation of the results presented so far, the $Top4$ index is positively correlated with modification rates of portfolio loans (column 1), but it is not correlated with the likelihood that securitized loans are renegotiated (column 2). Both results are reassuring, because securitized mortgages are held by dispersed investors and their probability of modification should be unrelated to the concentration of outstanding mortgages on lenders' balance sheets. The difference in the estimated coefficients in column 1 and 2 suggests that the renegotiation of portfolio loans in zip codes with higher outstanding mortgages concentration is unlikely to depend on omitted borrower or zip code characteristics. If this were

the case, modification rates for both securitized and portfolio loans would respond similarly to changes in the $Top4$ index.

3.3 Differences across zip codes

This subsection provides additional evidence consistent with a casual mechanism running from the concentration of outstanding mortgages on lenders' balance sheets to foreclosure rates.

To start with, a causal interpretation of our findings would imply that the $Top4$ index is associated with lower foreclosure rates in zip codes with higher delinquency rates. A stronger negative correlation in areas with lower delinquency rates would otherwise suggest that our findings are likely to be driven by ex ante differences in borrowers' quality. In column 1 of Table 5, we interact $Top4$ with a dummy variable that takes a value equal to one if the zip code has a delinquency rate above the median of our sample, and zero otherwise. Consistent with a causal effect, we find that the negative effect of $Top4$ on foreclosure rates is stronger when we focus on the subset of zip codes with more mortgage delinquencies.

In column 2, we distinguish between zip codes with different house price dynamics. As shown by Mian and Sufi (2011), areas with inelastic housing supply experienced the largest house price boom between 2004 and 2006, and suffered the largest decline in prices when house prices reversed in 2007. To ensure that the effect of the $Top4$ index on foreclosure rates is not due to unobservable factors related to the dynamics of local house prices, we test whether its effect varies across zip codes in MSAs with housing supply elasticity above and below the sample median. We measure housing supply elasticity using the Saiz (2010) index, which quantifies restrictions to the supply of new housing due to geographical constraints. The estimates in column 2 show that our main findings are unrelated to factors that explain booms and busts in house prices, such as lending to riskier borrowers.

In column 3 we explore nonlinearities in the relationship between the concentration of outstanding mortgages and foreclosure rates. We expect the negative effect of $Top4$ on foreclosure rates to be stronger in zip codes with higher concentration. The estimates in column 3 confirm that the negative effect of the $Top4$ index on foreclosure rates is stronger in areas with higher outstanding mortgage concentration (top tercile of the $Top4$ index distribution) than in lower outstanding mortgage concentration areas (bottom tercile).

3.3.1 Mortgage concentration and judicial foreclosure

Lenders' propensity to foreclose on mortgages is also likely to depend on local foreclosure laws. In the United States, some states require that a foreclosed sale takes place through

the court (judicial foreclosure states), while other states give lenders the automatic right to sell the property of the defaulting borrower (power-of-sale states). As discussed by Pence (2006), judicial procedures impose higher costs and lengthier foreclosure timelines on lenders. Accordingly, lenders' incentives to foreclose should be weaker in judicial foreclosure states regardless of their share of outstanding mortgages.

We use two metrics to capture procedural variation in foreclosure practices across jurisdictions. From Rao and Walsh (2009), we obtain the list of states where lenders must receive a judge's approval to foreclose (judicial foreclosure states). From Cutts and Merrill (2008), we obtain information on the estimated number of days required to accomplish a foreclosure, another proxy for the overall cost of a foreclosure procedure. We expect a stronger effect of $Top4$ on foreclosure rates in the subsample of zip codes located in power-of-sale states, and with an average length of time required to accomplish a foreclosure below the cross-sectional median.

Table 5 presents the estimates. Consistent with our conjectures, $Top4$ has a muted effect on foreclosure rates in the subsamples of zip codes where foreclosure procedures are more costly (columns 3 and 4). In column 5 and 6, we split the sample of zip codes in counties that abut judicial and non-judicial states. This split is useful because unobservable differences between zip codes near a state border are presumably minimal, which helps controlling for omitted variables. The point estimates imply that $Top4$ reduces foreclosures only in zip codes located in states with low foreclosure costs. These are important results as lenders that keep mortgages on their balance sheets should have stronger incentives to originate mortgages of better quality in judicial foreclosure states than in power of sale states. The reason is that lenders' payoffs in case of borrowers' defaults is likely to be lower in judicial states. Thus, any endogeneity problem related to the ex ante quality of mortgages should bias the results against our findings.

3.4 Lender characteristics

Another important concern is that our main findings may depend on lender characteristics that correlate with the $Top4$ index. For example, lenders' ability to collect soft information on borrowers' quality may affect their incentives to hold mortgages on their balance sheets. As a result, the negative correlation between $Top4$ and foreclosure rates is not attained because of lenders' incentives to mitigate foreclosure externalities ex post, but rather it may reflect lenders' ability to select borrowers of better quality ex ante. In this subsection, we provide evidence that observable lenders characteristics do not explain why zip codes where lenders hold a larger share of outstanding mortgages experience lower foreclosure rates. The next

subsection provides additional evidence using lender fixed effects in loan-level regressions to dismiss the concern that unobservable lender characteristics are responsible for our main results.

Loutskina and Strahan (2011) show that the geographical diversification of a lender's mortgage portfolio across MSAs is inversely correlated with the lender's investment in private information, which in turn may correlate with mortgage quality at origination. To evaluate the merit of this alternative explanation, we follow Loutskina and Strahan (2011) and compute the average portfolio diversification for all lenders in a zip code. The results are reported in column 1 of Table 6, where we also control for other lenders' characteristics, such as bank capital, ROA and bank's size.[18] We find that the effect of $Top4$ on foreclosure rates is unaffected, suggesting that private information and the ex ante quality of mortgages are unlikely to play a role in our findings.

The lending technology and its reliance on private, especially soft, information is also known to be correlated with lenders' size (Berger, Miller, Petersen, Rajan, and Stein, 2005), with small lenders being more able to acquire soft information than large lenders. If zip codes with small lenders were to have higher outstanding mortgage concentration, then the soft information of these lenders, rather than their ex post incentives, may allow them to renegotiate loans more easily, and even improve their ex ante lending decisions. To dismiss this alternative interpretation of our findings, column 2 in Table 6 controls for the concentration of mortgages retained by small commercial banks, defined as commercial banks with asset size in the bottom quartile of the asset size distribution. The estimates suggest that, if anything, foreclosures are more likely in zip codes in which small banks have also higher concentration of outstanding mortgages.

3.5 Unobservable lender characteristics

Despite the robustness of our results, a remaining concern is that some unobserved lenders' characteristics, such as organizational structures and renegotiation capabilities, may correlate with the $Top4$ index. To put this additional concern to rest, we use loan level data and run regressions with lenders fixed effects. Such regressions allow us to check whether a given lender's propensity to foreclose is higher in zip codes where the lender holds a lower share of outstanding mortgages on its balance sheet.

For this purpose, we merge HMDA information on mortgage originations with LPS information on mortgage performance.[19] Specifically, we focus on loans originated between 2004

[18] Average zip code bank capital, ROA and size are computed using the share of mortgages originated by each lender in a zip code as weight.

[19] The proprietary nature of LPS requires that lender identifiers are replaced with randomly generated

and 2006, and keep track of their performance between 2007 and 2010. We classify a loan as delinquent if LPS reports a delinquent status for the loan at least once between 2007 and 2010, and as foreclosed, if LPS records that a lender has started a foreclosure procedure on the loan at least once during the same period.

We estimate the following linear probability model:

$$\Pr\left(For \mid Delinquency\right)_{i,l,z,07-10} = \alpha Ret_{l,z,04-06} + \beta X_{i,z,04-06} + \delta_l + \epsilon_{i,l,z,07-10},$$

where $\Pr\left(For \mid Delinquency\right)_{i,l,z,07-10}$ denotes the probability that loan i originated and retained by lender l in zip code z is foreclosed during the period 2007–2010 conditional on being 90 or more days delinquent. The main variable of interest is:

$$Ret_{l,z,04-06} \equiv \frac{MR_{l,z}}{TotalOriginations_z},$$

which measures lender's l share of loans retained in zip code z during the 2004-2006 period.[20]

Our hypothesis is that $\alpha < 0$. That is, conditional on default, the probability that a mortgage is foreclosed is negatively related to the lender's share of outstanding mortgages in zip code z. The regression model is estimated holding constant a vector, $X_{i,z,04-06}$, of loan level controls at origination, such as the borrower's credit score, the loan to value ratio, the debt to income ratio, the loan subprime status, and the borrower's ethnicity. Importantly, the regression model includes lender fixed effects, δ_l , to ensure that unobserved lenders' characteristics do not drive the relationship between Ret and the probability that a delinquent portfolio loan, originated in the same zip code, is foreclosed.

The results are reported in Table 7. The estimates in column 1 confirm that conditional on delinquency, the probability that loan i in zip code z is foreclosed is negatively correlated with the share of mortgages in the same zip code that the lender retained on its balance sheet. In column 2, we look for non-linear effects. We find that the negative effect of $Ret_{l,z,04-06}$ on the probability of foreclosure is stronger for lenders in the top tercile of the $Ret_{l,z,04-06}$ distribution. These lenders are 6 percentage points less likely to foreclose a given loan than other lenders. This result reinforces the interpretation that lenders' decisions to foreclose depend on their incentives to internalize foreclosure externalities due to the share of mortgages they retained in the local housing market.

In column 3, we include several zip code level controls to ensure that our results are

identifiers. This implies that the HMDA-LPS dataset cannot be merged with other lenders information (for instance, from the Call Reports).

[20] We continue to consider only mortgages originated in the first three quarters because HMDA records whether the loan has been securitized at the end of the year. Since the process of securitization takes on average two months, loans issued in the last quarter could be inappropriately classified as retained.

not due to observable differences across markets. We find that the inclusion of these controls changes only marginally the magnitude of the estimated effect of $Ret_{l,z,04-06}$ on the foreclosure probability. Finally, in column 4, we consider the probability of foreclosure for securitized mortgages. As expected, we find that the proportion of loans that the lender originating the securitized mortgage has retained on its balance sheet is not related to the probability of foreclosing securitized mortgages.

4 House prices and outstanding mortgage concentration

In this section, we study the implications of lenders' incentives to foreclose on house prices. If an increase in $Top4$ is associated with lower foreclosure rates and foreclosures adversely affect local house prices, house prices changes should be positively correlated with the concentration of outstanding mortgages in a neighborhood. Table 8 tests this prediction with the same empirical framework used in the zip code level analysis of foreclosures in Section 3. We estimate the effect of $Top4$ on changes in house prices between 2007 and 2010 including county fixed effects and an array of controls for the local determinants of house prices.

As shown in column 1 of Table 8, the estimated coefficient of $Top4$ is positive and statistically significant. In column 2, a two-standard-deviation increase in $Top4$ is associated with a 22 percent lower house price depreciation for an average zip code. This result is obtained controlling for fraction of loans securitized, and remains unaffected if we also control for the average number of loans originated during the 2004-2006 period and the fraction of high cost loans. In column 3, we decompose the $Top4$ index into the fraction of loans retained by the four biggest holders, $Top4\_ret$, and the fraction of loans securitized, as we did in column 3 of Table 3. We continue to find that a higher concentration of outstanding mortgages is associated with a lower decrease in house prices during the 2007-2010 period.

Finally, in columns 4 and 5, we exploit the variation in $Top4$ and house price across states with different foreclosure procedures. As argued above, any lender should have weaker incentives to foreclose if the foreclosure process requires a judicial intervention or the process is relatively slow. Our estimates provide further support for this prediction, as the relationship between $Top4$ and the change in house prices is weaker in jurisdictions with costly foreclosure procedures.

5 Conclusion

We show that in markets with low outstanding mortgage concentration, lenders exhibit an excessive propensity to foreclose because they do not internalize the effects of foreclosures on house prices. We provide evidence supporting this mechanism using cross-sectional differences in foreclosures, renegotiations of delinquent mortgages, house prices and the concentration of outstanding mortgages across zip codes during the recent U.S. housing market crisis. We find that markets with high concentration of outstanding mortgage experience fewer foreclosures and smaller house price declines.

These findings have important policy implications. When shocks limit borrowers' ability to repay, measures favoring the consolidation of impaired mortgage lenders with similar geographic exposure may increase the concentration of outstanding mortgages. Our findings suggest that these measures may reduce lenders' aggregate losses because they tend to strengthen their incentives to renegotiate defaulting loans. Similar effects may be achieved with the creation of bad banks that collect troubled loans at times of crises.

The mechanism highlighted in this paper has bearings beyond the context of the housing market. It has implications for the price volatility of any collateralized market with dispersed lending structure. Exploring other areas in which lenders with a high share of the outstanding claims internalize the externalities created by liquidation decisions is an exciting avenue for future research.

References

[1] Adelino, M., K. Gerardi, and P. S. Willen. 2013. Why Don't Lenders Renegotiate More Home Mortgages? The Effect of Securitization. *Journal of Monetary Economics* 60, 835-853.

[2] Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, and D. Evanoff, 2011. The Role of Securitization in Mortgage Renegotiation, *Journal of Financial Economics* 102, 559-578.

[3] Agarwal, S., Y. Chang, and A. Yavas. 2012. Adverse Selection in Mortgage Securitization. *Journal of Financial Economics* 105, 640–660

[4] Agarwal, S., G., Amromin, I. Ben-David, S. Chomsisengphet, T. Piskorski and A. Seru, 2013. Policy Intervention in Debt Renegotiation: Evidence from Home Affordability Modification Program. Federal Reserve Bank of Chicago, W.P 2013-27.

[5] Anenberg, E., and E. Kung, 2014. Estimates of the Size and Source of Price Declines due to Nearby Foreclosures. *American Economic Review*, 104(8): 2527-51.

[6] Asquith, P., R. Gertner, and D. S., Scharfstein. 1994. Anatomy of Financial Distress: An Examination of Junk Bond Issuers. *Quarterly Journal of Economics*, 109(3): 625–58.

[7] Avery, R. B., K. P. Brevoort, and G. B. Canner, 2007. Opportunities and Issues in using HMDA Data, *Journal of Real Estate Research*, 29, 351-380.

[8] Benmelech, E. and N. Bergman, 2008. Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from U.S. Airlines. *Quarterly Journal of Economics* 123(4): 1635-1677.

[9] Benmelech, E. and N. Bergman, 2011. Bankruptcy and the Collateral Channel. *Journal of Finance* 66(2): 337-378.

[10] Berger, A. N., N. H. Miller, M.A. Petersen, R. G. Rajan, and J.C. Stein, 2005. Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks, *Journal of Financial Economics* 76, 237–269.

[11] Brunnermeier, M. K., and L. H. Pedersen, 2009. Market Liquidity and Funding Liquidity *Review of Financial Studies*, 22, 2201–38.

[12] Campbell, J. Y., S. Giglio, and P. Pathak, 2011. Forced Sales and House Prices, *American Economic Review* 101, 2108-2131.

[13] Coval J. and E. Stafford, 2007. Asset Fire Sales (and Purchases) in Equity Markets, *Journal of Financial Economics* 86 (2007) 479–512

[14] Cutts, A. C. and W. Merrill, 2008. Interventions in Mortgage Default: Policies and Practices to Prevent Home Loss and Lower Costs. Borrowing to Live: Consumer and Mortgage Credit Revisited. Working Paper, Freddie Mac.

[15] Elul, R., N. Souleles, S. Chomsisengphet, D. Glennon, and R. Hunt, 2010. What "Triggers " Mortgage Default, *American Economic Review* 100(2), 490-494.

[16] Favara, G. and J. Imbs, 2014. Credit Supply and the Price of Housing, *American Economic Review*, forthcoming.

[17] Fisher, L. M, L. Lambie-Hanson, and P. S. Willen, 2014. The Role of Proximity in Foreclosure Externalities. Evidence from Condominiumns, NBER Working Paper 20080.

[18] Garmaise, M., and T. Moskowitz, 2006. Bank mergers and crime: The real and social effects of credit market competition, *Journal of Finance* 61, 495–538.

[19] Ghent, A. C., 2011. Securitization and Mortgage Renegotiation: Evidence from the Great Depression, *Review of Financial Studies* 24, 1814–1847.

[20] Gromb D. and D. Vayanos, 2002. Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs. *Journal of Financial Economics* 66,: 361–407.

[21] Guiso, L., P. Sapienza, and L. Zingales, 2013. The Determinants of Attitudes towards Strategic Default on Mortgages, *Journal of Finance* 68, 1473–1515.

[22] Guren, A. and T. McQuade, 2013. How Do Foreclosures Exacerbate Housing Downturns?, Working Paper, Harvard University.

[23] Harding, J. P., E.Rosenblatt, and V. W. Yao, 2008. The Contagion Effect of Foreclosed Properties, *Journal of Urban Economics* 66, 164-178.

[24] Hartley, D., 2014. Regional Science and Urban Economics, *Regional Science and Urban Economics* 49, 108–117.

[25] Jiang, W., A. A. Nelson, and E. Vytlacil, 2014. Securitization and Loan Performance: Ex Ante and Ex Post Relations in the Mortgage Market. *Review of Financial Studies*, 27(2), 454–483.

[26] Keeley, Michael, 1990. Deposit Insurance, Risk and Market Power in Banking, *American Economic Review* 80, 1183-1200.

[27] Keys, B., T. Mukherjee, A. Seru, and V. Vig, 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans 2001-2006, *Quarterly Journal of Economics* 125, 307-62.

[28] Kiyotaki, N. and J. Moore, 1997. Credit Cycles. *Journal of Political Economy* 105 (2): 211–248.

[29] Levitin, A., and T. Twomey, 2011. Mortgage Servicing. *Yale Journal on Regulation* 28 (1), 2-90.

[30] Loutskina, E., and P. E. Strahan, 2011. Informed and Uninformed Investment in Housing: The Downside of Diversification, *Review of Financial Studies* 24, 1447–1480.

[31] Mayer, C., K. Pence, and S. M. Sherlund, 2009. The Rise in Mortgage Defaults. *Journal of Economic Perspectives*, 23(1): 27-50.

[32] Mayer, C., E. Morrison, T. Piskorski, and A. Gupta. 2014. Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide. *American Economic Review*, 104(9): 2830-57.

[33] Mian, A., and A. Sufi, 2009. The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis, *Quarterly Journal of Economics* 124, 1449–1496.

[34] Mian, A. R. and A. Sufi, 2011. House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis, *American Economic Review* 101, 2132–2156

[35] Mian, A., A. Sufi, and F. Trebbi, 2014. Foreclosures, House Prices, and the Real Economy, *Journal of Finance*, forthcoming.

[36] Piskorski, T., A. Seru, and V. Vig, 2010. Securitization and Distressed Loan renegotiation. Evidence from the Subprime Mortgage Crisis, *Journal of Financial Economics* 97, 369–397.

[37] Purnanandam, A., 2011. Originate-to-distribute Model and the Subprime Mortgage Crisis, *Review of Financial Studies* 24, 1881–1915.

[38] Pulvino, T., 1998. Do Asset Fire-Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions. *Journal of Finance*. 53(3): 939-979.

[39] Rao, J., and G. Walsh, 2009. Foreclosing a Dream: State Laws Deprive Homeowners of Basic Protections, Technical Report. Boston, MA: National Consumer Law Center.

[40] Rosen, R. J., 2011. Competition in Mortgage Markets: The Effect of Lender Type on Loan Characteristics, Economic Perspectives, 2–21.

[41] Saiz, A., 2010. The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics* 125, 1253–1296.

[42] Scharfstein, D. S., and A. Sunderam, 2014. Market Power in Mortgage Lending and the Transmission of Monetary Polity. mimeo

[43] Shleifer, A., Vishny, R., 1992. Liquidation Values and Debt Capacity: a Market Equilibrium Approach. *Journal of Finance* 47, 1343–1366.

[44] Shleifer, A., and R. Vishny, 2011. Fire Sales in Finance and Macroeconomics, *Journal of Economic Perspectives* 25(1), 29-48.

Fig. 1 2004-2006 Nationwide Distribution of Top 4 Index

distribution computed for 6,570 zip codes

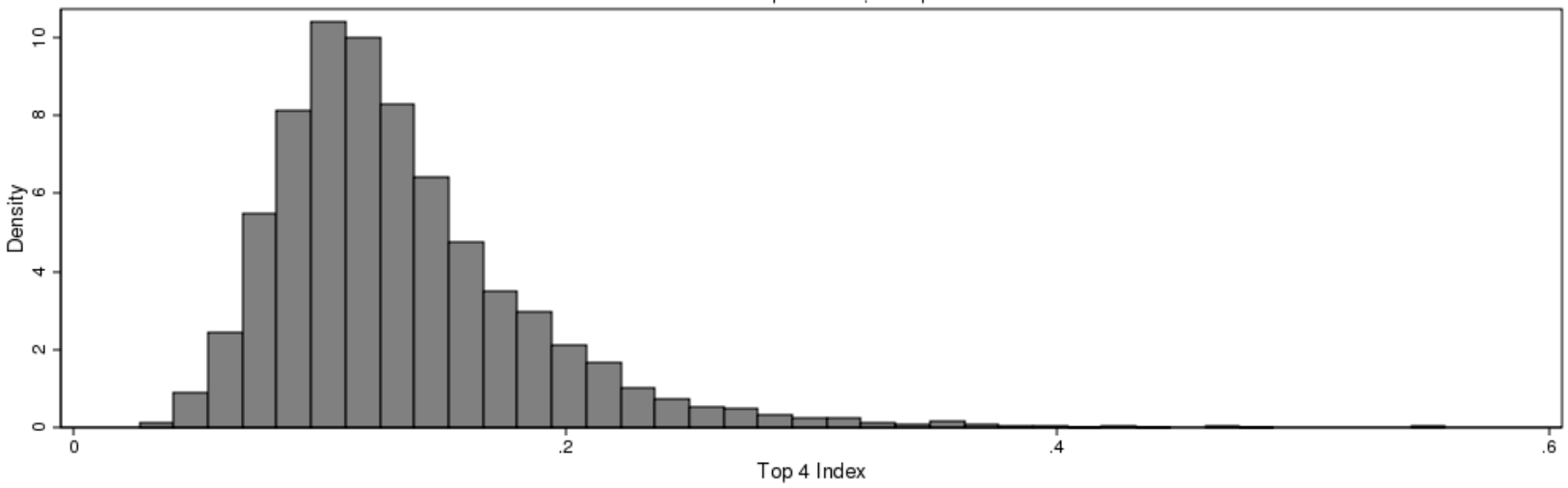

Fig. 2 2004-2006 Nationwide Distribution of Top 4 retained Index

distribution computed for 6,570 zip codes

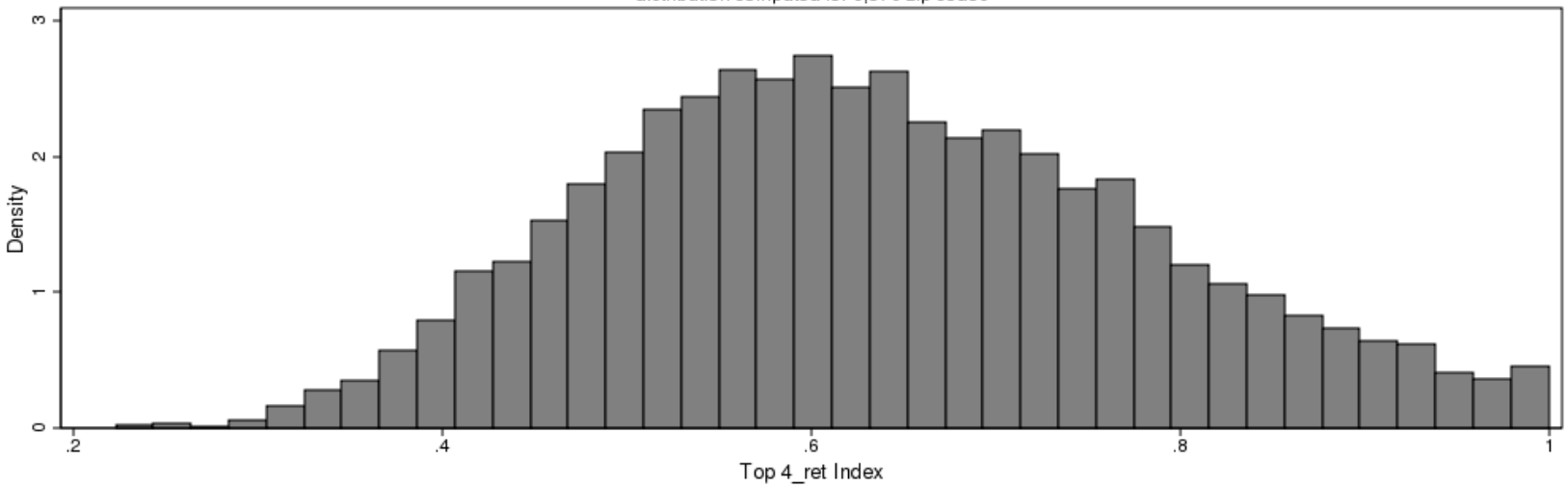

Table 1
Variable Definitions and Summary Statistics

This table provides definitions and descriptive statistics for the main variables used in the empirical analysis.

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
90+ Delinquencies	Zip code number of outstanding mortgages that are 90 days or more delinquent divided by number of outstanding mortgages. Average from 2007 to 2010.	Equifax	0.0258	0.0078	0.0543	0.0197	6534
Bank Capital	Bank average equity capital ratio in a zip code between 2007 and 2010. The weights used to compute the average are based on the number of mortgages originated by each bank in a given zip code.	Call Report	0.1025	0.0863	0.1217	0.0177	6259
Bank ROA	Bank average return on assets in a zip code between 2007 and 2010. The weights used to compute the average are based on the number of mortgages originated by each bank in a given zip code.	Call Report	0.0328	0.0290	0.0371	0.0058	6259
Bank Size	Bank average of the logarithm of assets in a zip code between 2007 and 2010. The weights used to compute the average are based on the number of mortgages originated by each bank in a given zip code.	Call Report	19.0834	17.1037	20.6052	1.7496	6259
Days Dummy	Dummy variable that takes value equal to one if the average length of time required to accomplish a foreclosure for zip codes in a given state is larger than the cross sectional median number of days for a foreclosure to be completed.	Crews Cutts and Merrill (2008)	0.5096	0	1	0.4999	6570
FICO score	Average risk core in a zip code (divided by 100) between 2004 and 2006.	Equifax	6.9286	6.4539	7.3551	0.3495	6506
Foreclosures, standardized by the number of housing units	The zip code's number of foreclosures, averaged from 2007 to 2010, divided by the number of single family, owner occupied housing units in the zip code in 2000. Foreclosures are defined as the sum	RealtyTrac.com and U.S Census Bureau	0.0198	0.0014	0.0489	0.0273	6159

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
	of notices of trustee sale and notices of sales.						
Foreclosures, standardized by number of 90 days + delinquencies	The zip code's number of foreclosures, averaged from 2007 to 2010, divided by the number of 90 days+ delinquencies in the zip code averaged over the same period. Foreclosures are defined as the sum of notices of trustee sale and notices of sales. 90 days+ delinquencies in the zip code are computed from Equifax that surveys 5% of the population, by dividing the number of 90 days + delinquencies in the zip code by 0.05.	RealtyTrac.com and Equifax	0.1405	0.0217	0.3045	0.1164	6505
GSE Securitization	The zip code's fraction of loans originated for purchase of single family owner occupied houses sold within the year of origination to government-sponsored housing enterprises. Average between 2004 and 2006.	HMDA	0.3555	0.2626	0.4504	0.0765	6570
High cost mortgages	Fraction of mortgages originated with mortgage rates 3 percentage points above the rate of a comparable maturity Treasury security. Average between 2004 and 2006.	HMDA	0.2163	0.0687	0.4125	0.1360	6570
House price growth	Logarithmic change between 2007 and 2010 of the zip code house price index for single-family owner-occupied houses.	CoreLogic	-0.2411	-0.5320	-0.0341	0.1878	6420
Judicial Foreclosure	Dummy variable that takes value equal to one for zip codes in states with a judicial requirement for foreclosures.	Rao and Walch (2009)	0.5339	0	1	0.4989	6570

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
Top 4	Ratio of the number of mortgages retained by the top 4 holders in a zip code, divided by the total number of mortgages originated in that zip code. Loans originated and retained are measured from 2004 to 2006. Loans are conventional mortgages for purchase of single-family owner-occupied houses. Lenders include commercial banks, thrifts, credit unions and mortgage companies.	HMDA	0.1331	0.0790	0.1997	0.0535	6570
Top 4_ret	Defined as Top 4, but considering only the number of loans originated and retained in a zip code to compute the denominator.	HMDA	0.6356	0.4502	0.8391	0.1463	6570
Top 4-Small Banks	Defined as Top 4, but considering only the number of loans originated and retained in a zip code by small commercial banks, defined as banks in the lowest quartile of the distribution for asset size.	HMDA	0.0570	0.0076	0.1367	0.0613	6564
Lagged HPI	Logarithm of the real zip code house price index for single-family owner-occupied houses. Average between 2004 and 2006.	CoreLogic	5.1479	4.7886	5.5033	0.2753	6420
Lender Diversification	Zip code average from 2004 to 2006 of the lender diversification index, defined as the sum of squared shares for the mortgages originated by each lender in each MSAs, relative to the total number of loans originated by same lender. Lenders include commercial banks, thrifts, credit unions and mortgage companies.	HMDA	0.0638	0.0118	0.1348	0.0589	6536
LTV ratio	Average from 2004 to 2006 of the loan to value ratio in a zip code.	Lender Processing Services (LPS)	0.7833	0.7378	0.8262	0.0390	6063
Median Income	Logarithmic median income in the zip code in 2000.	U.S. Census Bureau	10.9509	10.5412	11.3671	0.3279	6570

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
Minorities	The percentage of Black and Hispanic in the zip code in 2000.	U.S. Census Bureau	0.2231	0.0280	0.5840	0.2276	6185
Mortgage per capita	The value of first mortgages and home equity lines outstanding in the zip code divided by the number of households (divided by 100,000). Average between 2004 and 2006.	Equifax	0.6811	0.2618	1.2288	0.4290	6506
Non-GSE securitization	The zip code's fraction of loans originated for purchase of single family, owner occupied housing units sold to non-government-sponsored housing enterprises within the year of origination. Average between 2004 and 2006.	HMDA	0.3920	0.2892	0.4951	0.0822	6570
Origination	Average of the number of loans originated between 2004 and 2006, divided by the number of single family, owner occupied housing units in the zip code in 2000.	HMDA and U.S. Census Bureau	0.0645	0.0049	0.0471	2.3209	6185
Population	The logarithm of the zip code's population in 2000.	U.S. Census Bureau	8.4719	8.0953	8.8649	0.3325	6570
Renegotiations-Portfolio Loans	Number of modifications for mortgages held on lenders' balance sheets that are 60 days delinquent, divided by the total number of defaulting loans. Zip code average between 2007 and 2010. Modifications refer to a change in mortgages' interest rates, principal balances and loan terms, using the algorithm developed by Adelino, Gerardi and Willen (2013).	Lender Processing Services (LPS)	0.0242	0.0000	0.0546	0.0270	6548
Renegotiations-Securitized Loans	Defined as Renegotiations-Portfolio Loans, but considering renegotiations of securitized loans at the numerator.	Lender Processing Services (LPS)	0.1412	0.0611	0.2314	0.0814	6548

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
Securitization	The zip code's fraction of loans originated for purchase of single family, owner occupied housing units sold within the year of origination to other non-affiliated financial institutions or government-sponsored housing enterprises. Average between 2004 and 2006.	HMDA	0.7476	0.6493	0.8260	0.0767	6570
Subprime Borrowers	Fraction of households in a zip code with FICO score below 620. Average between 2004 and 2006.	Equifax	0.1103	0.0310	0.2159	0.0810	6489

Table 2
Foreclosures

Cross-sectional zip code level regressions of the number of foreclosures, standardized by the number of houses in the zip code (in columns 1 to 3), and by the number of 90 days + delinquent loans (in columns 4 to 6) on the main proxy for outstanding mortgage concentration. All variable definitions and sources are reported in Table 1. Regressions include MSA fixed effects in columns 1 and 4, county fixed effects in columns 2 and 5, and county subdivision fixed effects in columns 3 and 6. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Foreclosures					
	Standardized by the Number of Houses			Standardized by the number of 60+ days delinquencies		
Top 4	-0.054***	-0.068***	-0.094***	-0.205***	-0.193***	-0.198***
	(0.013)	(0.014)	(0.025)	(0.046)	(0.042)	(0.072)
Securitization	0.029***	0.037***	0.037***	0.052*	0.033	0.004
	(0.008)	(0.007)	(0.013)	(0.031)	(0.029)	(0.052)
90+ Delinquencies	0.680***	0.689***	0.674***	-2.215***	-2.266***	-2.282***
	(0.086)	(0.091)	(0.150)	(0.240)	(0.238)	(0.305)
Fico score	-0.012***	-0.011***	-0.015**	-0.008	-0.013	-0.004
	(0.004)	(0.004)	(0.007)	(0.014)	(0.015)	(0.021)
%Subprime borrowers	0.002	0.003	0.001	0.360***	0.358***	0.336***
	(0.019)	(0.021)	(0.031)	(0.062)	(0.055)	(0.087)
LTV ratio	-0.015	-0.017	-0.015	0.058	0.024	0.040
	(0.014)	(0.014)	(0.026)	(0.040)	(0.039)	(0.075)
Mortgage per capita	0.028***	0.030***	0.036***	0.039***	0.043***	0.041***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.007)	(0.009)
Lagged HPI change	-0.025***	-0.020**	-0.023	-0.084***	-0.012	-0.001
	(0.008)	(0.010)	(0.015)	(0.027)	(0.024)	(0.039)
Lagged HPI	0.002	0.008	0.010	0.068***	0.078***	0.070**
	(0.005)	(0.006)	(0.012)	(0.019)	(0.017)	(0.029)
Population	-0.003**	-0.005***	-0.006*	-0.027***	-0.026***	-0.019**
	(0.002)	(0.002)	(0.003)	(0.006)	(0.005)	(0.008)
Income	-0.018***	-0.022***	-0.024***	-0.079***	-0.098***	-0.095***
	(0.004)	(0.004)	(0.008)	(0.012)	(0.013)	(0.019)
Minorities	-0.012**	-0.012**	-0.009	0.065***	0.047***	0.076***
	(0.005)	(0.005)	(0.008)	(0.016)	(0.017)	(0.021)
Constant	0.285***	0.301***	0.349***	0.886***	1.104***	0.993***
	(0.055)	(0.059)	(0.112)	(0.193)	(0.200)	(0.289)
Fixed Effects	MSA	County	County Subdivisions	MSA	County	County Subdivisions
Obs.	5655	5655	5655	5654	5654	5654
R^2	.679	.72	.809	.668	.765	.857

Table 3
Securitization and the Concentration of Outstanding Mortgages

Cross-sectional zip code regressions of the foreclosure rate (Foreclosures) on the index of outstanding mortgage concentration. The number of foreclosures is standardized by the number of houses in the zip code. All variable definitions and sources are reported in Table 1. All regressions include county dummies. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively

	(1)	(2)	(3)
		Foreclosures	
Top 4	-0.068***	-0.065***	
	(0.014)	(0.013)	
Top 4 _ret			-0.046***
			(0.013)
Top 4 _ret ×Securitization			0.016
			(0.015)
Securitization		0.031***	0.039***
		(0.007)	(0.006)
Non GSE Securitization	0.042***		
	(0.008)		
GSE Securitization	0.032***		
	(0.008)		
High Cost Mortgages		-0.014	-0.006
		(0.011)	(0.011)
Origination		0.019***	0.019***
		(0.003)	(0.003)
90+ Delinquencies	0.683***	0.650***	0.622***
	(0.092)	(0.096)	(0.093)
Fico score	-0.010**	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)
%Subprime borrowers	0.003	0.026	0.024
	(0.021)	(0.022)	(0.021)
LTV ratio	-0.017	-0.018	-0.018
	(0.014)	(0.013)	(0.013)
Mortgage per capita	0.030***	0.024***	0.023***
	(0.004)	(0.004)	(0.004)
Lagged HPI change	-0.021**	-0.020**	-0.020**
	(0.010)	(0.009)	(0.009)
Lagged HPI	0.008	0.009*	0.008
	(0.006)	(0.005)	(0.005)
Population	-0.005**	-0.004**	-0.007***
	(0.002)	(0.002)	(0.002)
Income	-0.023***	-0.020***	-0.021***
	(0.004)	(0.004)	(0.004)
Minorities	-0.012**	-0.008	-0.005
	(0.005)	(0.005)	(0.005)
Constant	0.300***	0.255***	0.308***
	(0.059)	(0.057)	(0.059)
Obs.	5655	5655	5655
R2	.721	.744	.749

Table 4
Loan Modifications

Cross-sectional zip code level regressions for Renegotiations of Portfolio Loans (column 1), and Renegotiations of Securitized Loans (column 2) on the main proxy for outstanding mortgage concentration. All variable definitions and sources are reported in Table 1. Regressions include county fixed effects. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively.

	(1)	(2)
	Renegotiation	
	Portfolio Loans	Securitized loans
Top 4	0.046**	-0.056
	(0.020)	(0.046)
Securitization	-0.059***	0.011
	(0.012)	(0.024)
90+ Delinquencies	-0.062	-0.091
	(0.044)	(0.121)
Fico score	0.010***	0.061***
	(0.004)	(0.011)
%Subprime borrowers	0.092***	0.165***
	(0.012)	(0.038)
LTV ratio	-0.025	0.143***
	(0.016)	(0.050)
Mortgage per capita	0.007***	-0.014**
	(0.002)	(0.007)
Lagged HPI change	-0.005	0.008
	(0.006)	(0.018)
Lagged HPI	-0.014**	-0.043**
	(0.006)	(0.017)
Population	0.002	0.015***
	(0.002)	(0.004)
Income	0.004	0.039***
	(0.003)	(0.009)
Minorities	-0.001	0.009
	(0.004)	(0.013)
Constant	0.008	-0.750***
	(0.057)	(0.160)
Obs.	5671	5671
R^2	.338	.408

Table 5

Cross-Sectional Variation in the Effect of the Outstanding Mortgage Concentration

Cross-sectional zip code regressions of the foreclosure rate (Foreclosures) on the index of outstanding mortgage concentration. The number of foreclosures is standardized by the number of houses in the zip code. T2 Top 4 and T3 Top 4 are dummy variables that take value equal to 1 for zip codes that are respectively in the second and third terciles of the Top 4 index's distribution. All variable definitions and sources are reported in Table 1. All regressions include county dummies. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively

	(1)	(2)		(3)	(4)	(5)	(6)
			Whole Sample			Bordering Counties	
Top 4	-0.057***	-0.040**		-0.096***	-0.092***	-0.061**	-0.058**
	(0.013)	(0.018)		(0.016)	(0.016)	(0.028)	(0.028)
Top 4×High delinquency	-0.014**						
	(0.006)						
Top 4×High Elasticity		-0.038					
		(0.024)					
T2 Top 4			-0.002***				
			(0.001)				
T3 Top 4			-0.004***				
			(0.001)				
Top 4×Judicial foreclosures				0.052**		0.065**	
				(0.024)		(0.028)	
Top 4×Long foreclosures					0.057**		0.058*
					(0.024)		(0.030)
Securitization	0.031***	0.033***	0.042***	0.031***	0.030***	0.018**	0.017**
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)
High Cost Mortgages	-0.012	-0.012	-0.011	-0.015	-0.015	0.025*	0.025*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)
Origination	0.019***	0.019***	0.019***	0.019***	0.019***	0.044***	0.044***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
90+ Delinquencies	0.658***	0.650***	0.665***	0.649***	0.648***	0.147*	0.153*
	(0.097)	(0.096)	(0.097)	(0.096)	(0.096)	(0.086)	(0.086)
Fico score	-0.009**	-0.008**	-0.009**	-0.009**	-0.008**	-0.008	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
%Subprime borrowers	0.025	0.025	0.022	0.028	0.029	0.051**	0.053**
	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
LTV ratio	-0.016	-0.017	-0.015	-0.018	-0.018	-0.055***	-0.056***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.021)	(0.020)

	(1)	(2)		(3)	(4)	(5)	(6)
			Whole Sample			Bordering Counties	
Mortgage per capita	0.024***	0.024***	0.024***	0.025***	0.025***	0.012***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Lagged HPI change	-0.021**	-0.020**	-0.020**	-0.020**	-0.019**	-0.011*	-0.011*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)
Lagged HPI	0.009*	0.009*	0.009*	0.008	0.008	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Population	-0.004**	-0.004**	-0.003*	-0.004**	-0.004**	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income	-0.020***	-0.020***	-0.019***	-0.020***	-0.020***	-0.014**	-0.014**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Minorities	-0.008*	-0.007	-0.008*	-0.008*	-0.008	-0.011**	-0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.264***	0.250***	0.219***	0.264***	0.257***	0.219***	0.215***
	(0.059)	(0.056)	(0.056)	(0.056)	(0.057)	(0.063)	(0.063)
Obs.	5655	5655	5655	5655	5655	942	942
R2	.745	.745	.742	.745	.746	.798	.797

Table 6
Lender Characteristics and the Concentration of Outstanding Mortgages

Cross-sectional zip code regressions of the foreclosure rate (Foreclosures) on the index of outstanding mortgage concentration. The number of foreclosures is standardized by the number of houses in the zip code. All variable definitions and sources are reported in Table 1. All regressions include county dummies. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively

	(1)	(2)
Top 4	-0.067***	-0.077***
	(0.014)	(0.014)
Lender diversification	0.018	
	(0.016)	
Top 4-Small banks		0.042***
		(0.010)
Bank capital	0.031***	0.034***
	(0.007)	(0.007)
Bank ROA	-0.012	-0.013
	(0.011)	(0.011)
Bank size	0.019***	0.019***
	(0.003)	(0.003)
Securitization	0.646***	0.648***
	(0.096)	(0.096)
High Cost Mortgages	-0.009**	-0.009**
	(0.004)	(0.004)
Origination	0.026	0.027
	(0.022)	(0.021)
90+ Delinquencies	-0.018	-0.017
	(0.013)	(0.013)
Fico score	0.025***	0.025***
	(0.004)	(0.004)
%Subprime borrowers	-0.020**	-0.021**
	(0.009)	(0.009)
LTV ratio	0.009*	0.009*
	(0.005)	(0.005)
Mortgage per capita	-0.004**	-0.004**
	(0.002)	(0.002)
Lagged HPI change	-0.020***	-0.019***
	(0.004)	(0.004)
Lagged HPI	-0.007	-0.007
	(0.005)	(0.005)
Population	0.257***	0.253***
	(0.056)	(0.056)
Income	-0.020***	-0.020***
	(0.004)	(0.004)
Minorities	-0.006	-0.006
	(0.005)	(0.005)
Constant	0.258***	0.254***
	(0.056)	(0.056)
Obs.	5655	5652
R2	.745	.746

Table 7
Lender's Propensity to Foreclose and Fraction of Outstanding Mortgages

Panel A. Summary Statistics

This table provides definitions and descriptive statistics for the main variables used in the loan level regressions estimated in Panel B.

Variable Name	Variable Description	Source	Mean	p10	p90	sd	Obs.
Black-Hispanic borrower	Dummy variable equal to 1 if the borrower is Black or Hispanic, and zero otherwise.	HMDA	0.403	0	1	0.490	143,647
Borrower debt to income	Borrower's debt to income ratio at origination	LPS	36.26	21	49	11.316	143,647
Borrower fico score	Borrower's loan to value ratio at origination	LPS	689.87	620	763	56.024	143,647
Foreclosure portfolio loans	Foreclosure probability of portfolio loans conditional on being 90 plus days delinquent.	LPS	0.612	0	1	0.487	27,011
Foreclosure securitized loans	Foreclosure probability of securitized loans conditional on being 90 plus days delinquent.	LPS	0.738	0	1	0.439	116,636
High cost loan	Dummy variable equal to one if the loan is originated with an interest rates 3 percentage points above the rate of a comparable maturity Treasury security, and zero otherwise.	HMDA	0.234	0	1	0.423	143,647
Interest-only loan	Dummy variable equal to one if the loan is interest only, and zero otherwise.	LPS	0.301	0	1	0.459	143,647
Loan LTV ratio	Borrower's loan to value ratio at origination	LPS	81.75	74.67	96.71	9.161	143,647
$Ret_{04\text{-}06}$ portfolio loans	Number of mortgages retained by lender *l* in zip code *z* as a fraction of the total number of mortgages originated in the same zip code between 2004 and 2006. Sample of portfolio loans only.	HMDA	0.027	0.004	0.052	0.029	27,011
$Ret_{04\text{-}06}$ securitized loans	Number of mortgages retained by lender *l* in zip code *z* as a fraction of the total number of mortgages originated in the same zip code between 2004 and 2006. Sample of securitized loans only.	HMDA	0.007	0	0.022	0.013	116,636

Panel B. Results

Loan level regressions for the probability that a delinquent loan is foreclosed. The dependent variable is a dummy variable that takes a value equal to 1 if a delinquent loan has been foreclosed during 2007-2010 and equal to zero otherwise; only loans that have been delinquent 90 days or more during this period are considered. All variables are defined in Panel A. In columns 1 to 3 we consider only portfolio loans; in column 4 we consider only securitized loans. T2 Ret_{04-06} and T2 Ret_{04-06} are dummy variables that take value equal to 1 if Ret_{04-06} is respectively in the second and third tercile of the distribution of Ret_{04-06} among portfolio loans. Standard errors in parenthesis are clustered at the zip code level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively.

	(1)	(2)	(3)	(4)
		Portfolio Loans		Securitized Loans
Ret_{04-06}	-0.6066***		-0.3679***	0.0407
	(0.1947)		(0.1141)	(0.1554)
T2 Ret_{04-06}		-0.0177		
		(0.0196)		
T3 Ret_{04-06}		-0.0580***		
		(0.0206)		
Loan level controls				
Borrower fico score	-0.0001***	-0.0001**	-0.0001**	-0.0001***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Loan LTV ratio	-0.0005	-0.0006*	-0.0007*	0.0011***
	(0.0003)	(0.0004)	(0.0004)	(0.0002)
Borrower debt to income	-0.0004	-0.0004	-0.0003	-0.0008***
	(0.0003)	(0.0003)	(0.0003)	(0.0001)
Interest-only loan	0.0135	0.0131	0.0279***	0.0363***
	(0.0083)	(0.0083)	(0.0083)	(0.0032)
High cost loan	0.1126***	0.1120***	0.0963***	0.0724***
	(0.0129)	(0.0129)	(0.0132)	(0.0036)
Black-hispanic borrower	-0.0094	-0.0116*	-0.0290***	0.0013
	(0.0066)	(0.0066)	(0.0069)	(0.0032)
Zip code level controls				
90+ Delinquencies			2.2838***	2.1250***
			(0.2726)	(0.1505)
Fico score			0.2050***	0.0714***
			(0.0266)	(0.0151)
%Subprime borrowers			0.3032***	-0.1058**
			(0.0980)	(0.0522)
LTV ratio			-0.1614	-0.4418***
			(0.1464)	(0.0844)
Mortgage per capita			-0.0615***	-0.0381***
			(0.0122)	(0.0069)
Lagged HPI change			0.1348***	0.0171
			(0.0272)	(0.0138)
Lagged HPI			-0.0982***	-0.0501***
			(0.0238)	(0.0120)
Population			-0.0035	0.0080
			(0.0117)	(0.0061)
Income			-0.0627***	-0.0608***
			(0.0214)	(0.0122)
Constant	0.7832***	0.8008***	0.6208*	1.4105***
	(0.0518)	(0.0557)	(0.3585)	(0.1879)
Obs	27011	27011	26115	111883
R2	.0840	.0841	.0938	.0548

Table 8
Change in House Prices and Outstanding Mortgage Concentration

Cross-sectional zip code level regressions of the logarithmic change in house prices between 2007 and 2010 on the index of outstanding mortgage concentration. All variable definitions and sources are reported in Table 1. The change in house price is computed considering an average of all the house sales in the zip code. All regressions include county dummies. Standard errors in parenthesis are clustered at the county level and corrected for heteroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Lagged Top 4	0.128***	0.107***		0.222***	0.165***
	(0.039)	(0.041)		(0.062)	(0.052)
Lagged Top 4_ret			0.107**		
			(0.044)		
Lagged Top 4 _ret ×Securitization			-0.089*		
			(0.049)		
Lagged Top 4×Judicial foreclosures				-0.188***	
				(0.065)	
Lagged Top 4×Long foreclosures					-0.121*
					(0.062)
Securitization	0.033	0.026	0.025	0.027	0.027
	(0.029)	(0.030)	(0.031)	(0.029)	(0.029)
High Cost Mortgages		-0.125***	-0.130***	-0.119***	-0.123***
		(0.030)	(0.030)	(0.029)	(0.029)
Origination		0.003	0.003	0.003	0.003
		(0.004)	(0.004)	(0.004)	(0.004)
90+ Delinquencies	-1.619***	-1.426***	-1.401***	-1.420***	-1.422***
	(0.198)	(0.187)	(0.189)	(0.186)	(0.187)
Fico score	0.009	0.004	0.004	0.006	0.004
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)
%Subprime borrowers	0.043	0.146***	0.146***	0.139***	0.139***
	(0.043)	(0.053)	(0.053)	(0.052)	(0.052)
LTV ratio	-0.010	0.009	0.010	0.009	0.010
	(0.040)	(0.040)	(0.040)	(0.041)	(0.041)
Mortgage per capita	0.017***	0.015***	0.015***	0.013**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Lagged HPI change	0.051**	0.049**	0.049**	0.047**	0.047**
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)
Lagged HPI	-0.051**	-0.048**	-0.047**	-0.045**	-0.047**
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Population	-0.000	0.000	0.003	0.001	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Income	-0.001	-0.004	-0.003	-0.004	-0.004
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Minorities	0.027*	0.037**	0.036**	0.039***	0.038**
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
Constant	-0.068	-0.016	-0.059	-0.047	-0.020
	(0.171)	(0.171)	(0.172)	(0.168)	(0.170)
Obs.	5671	5671	5671	5671	5671
R^2	.896	.897	.897	.897	.897