Mortgage Concentration, Foreclosures and House Prices*

Giovanni Favara
Board of Governors of the Federal Reserve System
giovanni.favara@frb.gov

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

April 17, 2014

*We thank Paul Kalem, Anastasia Kartasheva, Benjamin Keys, Elena Loutskina, Steven Ongena, Anthony Pennington-Cross, Amit Seru, Greg Udell, Vikrant Vig, and seminar participants at the Society for Economic Dynamics Conference in Seoul, the workshop on "Financial Intermediation, Risk and Liquidity Management" of the Barcelona GSE Summer Forum, the Board of Governors of the Federal Reserve System, the IBEFA Conference in Seattle, the Summer Meeting of the Econometric Society at the University of Southern California, the Conference on "Banks and Government in Globalized Markets" at the Austrian Central Bank, the Bocconi/Carefin Conference on "Financing the Recovery After the Crisis: The Roles of Bank Profitability, Stability and Regulation", the New York University Stern School of Business, the University of British Columbia Sauder School of Business, the University of Lausanne and EPFL, the University of Amsterdam, and the Goethe University in Frankfurt. 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.

Mortgage Concentration, Foreclosures and House Prices

Abstract

Previous research has shown that mortgage foreclosures generate a negative externality on nearby house prices. In this paper, we conjecture that lenders with a larger share of a neighborhood's outstanding mortgages on their balance sheets internalize this externality and are thus more inclined to renegotiate defaulting loans. We provide evidence supporting this conjecture using zip code level data on house prices and foreclosures during the 2007-2009 U.S. housing market crisis. We find that zip codes with larger outstanding mortgage concentration experienced fewer foreclosures and smaller house prices declines. These findings are not driven by prior local economic conditions, mortgage securitization or ex-ante lenders characteristics, and hold within geographical areas exposed to common economic shocks, such as MSAs or counties. We also find that the concentration of outstanding mortgages matters more in zip codes of non-judicial states where foreclosure procedures are less costly.

Keywords: House Prices; Foreclosures; Bank Concentration

JEL Codes: G01; G21; R31; R38

I Introduction

Liquidation of collateralized debt may generate pecuniary externalities that feed back on collateral values and may amplify the effects of negative shocks through price-default spirals (Shleifer and Vishny, 2011). This paper argues that lenders with larger exposures to outstanding collateralized debt are more likely to internalize liquidation externalities because they are prone to suffer larger losses due to asset value fluctuations.

We illustrate this point in the context of the recent U.S. housing market crisis. The recent housing crisis is an ideal setting as it features a sharp increase in mortgage defaults and foreclosures, and a steep decline in house prices. In addition, as shown by an increasing body of empirical research, there have been important feedback loops between foreclosures and house prices. For instance, Campbell, Giglio and Pathak (2011), Harding, Rosenblatt, and Yao (2009) and Anenberg and Kung (2013) show that foreclosures cause price declines of nearby homes through pecuniary and non-pecuniary externalities. In turn, generalized price declines may lead to more defaults and further price declines if borrowers with negative equity default strategically (Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010), or defaults affect the social norms for mortgage repayment (Guiso, Sapienza and Zingales, 2013), or, more generally, foreclosures reduce the amenities value of a neighborhood or impair its local market activity.

In this paper, we argue that the feedback loop between foreclosures and house prices is mitigated in neighborhoods where lenders hold larger shares of outstanding mortgages. The idea is that lenders more exposed to losses in a neighborhood anticipate that foreclosures create negative price-defaults spirals that ultimately feedback on their balance sheets. These lenders foreclose defaulting borrowers less often, and as a result their neighborhoods experience smaller house price declines. To clarify this idea, we first present a stylized model relating defaults, foreclosures, and housing prices in local markets with different lenders' mortgage concentration. We then use U.S. zip code level data to test the model's predictions.

In the model, negative income shocks make borrowers unable to repay their mortgage debt.

These liquidity defaults may lead to mortgage renegotiations or foreclosures depending on the lenders' stakes in the local mortgage market. When the provision of credit is dispersed, foreclosure decisions are taken in isolation, and (atomistic) lenders do not internalize that their liquidation decisions depress local housing prices. In these markets, liquidity defaults cause house prices declines, and are followed by strategic defaults, as borrowers with negative equity that can afford to repay find it optimal to default. In contrast, a lender that retains a large proportion of the outstanding mortgages internalizes the adverse effects of its liquidation decisions on house prices and strategic defaults, and has stronger incentives to renegotiate defaulting loans. More renegotiations reduce the adverse effects of negative shocks on the demand for housing leading to lower rates of house price depreciation, which in turn weaken borrowers' incentives to strategically default.[1]

To test the implications of this theory, we use differences in mortgage lending concentration, foreclosures, and house prices across U.S. zip codes during the 2004-2009 period. Zip codes are the finest geographical units for which we are able to explore price changes in a broad cross-section of areas and within which foreclosures are expected to have negative externalities on house prices. To control for factors that uniformly affect zipcodes within a county (or MSA), such as income shocks and ex ante lender competition, we only exploit within-county (or within-MSA) variation in outstanding mortgage concentration.

Consistent with the model's predictions, we find that after a negative income shock, house prices decline less in areas in which few lenders retained a large share of outstanding mortgages on their balance sheets: A one-standard deviation increase in the mortgage concentration index reduces the fall in house price associated with a negative income shocks by 4 percent.

These results are robust to the inclusion of standard controls for local housing, income and demographic characteristics, as well as for aggregate nationwide trends. The results are also robust to the use of alternative indexes of market concentration and to controls for differences in ex ante characteristics of the credit market. In particular, we find that our results are not driven by ex-ante

[1] Although in the model pecuniary externalities leads to strategic defaults, alternative mechanisms may lead foreclosures to depress local house prices, such as disamenity effects or a general weakening of local economic conditions.

differences across geographical areas in loan-to-value ratios, mortgages per capita, and proxies for borrower creditworthiness or bank characteristics.

To strengthen the interpretation of these findings, we test three additional implications of our theory. First, we study how mortgage concentration affects foreclosures and house price across U.S. states with different foreclosure procedures. As shown by Pence (2006) and Mian, Sufi, and Trebbi (2012), foreclosure decisions in the U.S. depend on the state laws. In particular, foreclosures are more frequent in non-judicial states where lenders have the automatic right to sell the property of a defaulting borrower. In contrast, there are fewer foreclosures in judicial states, where lenders must go through the courts to foreclose on a property. These judicial procedures entail higher transaction costs for lenders. We expect that any lender, regardless of its exposure to mortgages in a neighborhood, should have weaker incentives to foreclose in judicial states. Consistent with this idea, we find that the concentration of outstanding mortgages mitigate the effects of negative income shocks on house prices to a larger extent in in non-judicial states where foreclosure decisions are more likely.

Second, we show that the link between house prices and mortgage market concentration goes through lenders' propensity to foreclose defaulting loans. After a negative income shock, we estimate that more foreclosures occur in zip codes with more dispersed mortgage provision, and, consistent with the findings on house prices, the effect of mortgage concentration is stronger in jurisdictions where foreclosure procedures are less costly. Third, while mortgage concentration is associated with fewer foreclosures following negative income shocks, it is not associated with lower delinquency rates. This indicates that lenders with different ex post incentives to solve distress, are unlikely to differ in the ability to screen borrowers ex-ante.

We finally explore the role of securitization in driving our findings. Securitization tends to reduce the concentration of outstanding mortgages since securitized mortgages are best thought as held by atomistic lenders. Thus, the handling of mortgages by intermediaries (servicers) with weak organizational capabilities to conduct renegotiation (Piskorski, Seru and Vig (2010) and Agarwal et al. (2011)) may be viewed as an optimal contract between lenders and servicers because it is consistent with the ex post incentives of securitized lenders. However, securitization may lead to renegotiation frictions for reasons that are orthogonal to the one we propose, for instance if dispersed ownership (brought about by mortgage securitization) inhibits loan renegotiation.[2] For this reason, we show that our results continue to hold when we control for the proportion of securitized mortgages. This evidence reassures us that the effects of outstanding mortgage market concentration are distinct from those related to securitization.

Our paper contributes to the burgeoning literature scrutinizing the 2007-2009 real estate crisis. A number of papers explore how differences in the local mortgage markets are associated with the intensity of the crisis. Mian and Sufi (2009 and 2011) study how the mortgage supply expansion induced by securitization led to an increases in house prices and higher households' leverage across U.S. zip codes. Keys, Mukherjee, Seru and Vig (2010) and Keys, Seru and Vig (2012) show that securitization led to less intensive screening and higher default rates. Loutskina and Strahan (2011) highlight that the technology of lenders that diversify their mortgage portfolios across many MSAs involves less investment in private information. Here we focus on lenders' ex-post incentives and study the role of mortgage dispersion within a zip code, after controlling for households' indebtness and lenders' characteristics that may be related to lenders' incentives to acquire ex-ante information on the borrower.

An earlier strand of literature explores the effects of concentration on bank-firm relationships (Berger, Miller, Petersen, Rajan, and Stein, 2005) and loan supply (Garmaise and Moskowitz, 2006). Scharfstein and Sunderam (2013) argue that a significant increase in the concentration of mortgage origination has decreased the sensitivity of mortgage rates and refinancing activity to mortgage-backed security yields. All these papers study the effects of market concentration on the ex ante competition in the origination of loans and contract terms. We focus, instead, on the concentration of outstanding mortgages, as opposed to the concentration of mortgage origination. To the best of our knowledge, we are the first to highlight the role of market structure on lenders'

[2] By contrast, Adelino, Gerardi and Willen (2010a and b), and Ghent (2011) provide evidence that securitization is unlikely to be the main reason why lenders are reluctant to renegotiate mortgages.

liquidation incentives and asset prices. By showing that a market with dispersed lenders is more prone to fire sales, we also provide an alternative interpretation to the view that competition in the market for credit erodes financial stability because it lowers lenders' profits, distorting their risk-taking decisions (Keely, 1990).

The rest of the paper proceeds as follows. Section 2 introduces a simple theoretical framework. Section 3 describes the data used in the paper and the empirical strategy. Section 4 presents evidence supporting the mechanisms linking mortgage concentration to changes in house prices and foreclosures. Section 5 concludes the paper.

II Theory and Testable Implications

This section presents a simple model to illustrate the relationship between income shocks, foreclosures and house prices across local housing markets with different outstanding mortgage concentration. In the model, foreclosures cause a pecuniary externality, which magnifies the effect of negative income shocks on local housing prices. The pecuniary externality arises because households have incentives to default strategically when the value of their mortgages exceeds the value of their houses.[3]

A The model

A.1 Assumptions

We consider a one-period model with 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 $h_i \in \{0, 1\}$:

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

[3] The role of mortgage concentration highlighted in the model does not hinge on this specific mechanism leading to the pecuniary externality. We discuss other possible mechanisms when we introduce our empirical design.

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.

Housing supply is fixed at $\overline{H} < \overline{\gamma}$.

At $t = 1$ households receive a random income w_i, independently distributed from γ_i. With probability q , everyone receives w. With probability $1 - q$, a fraction e of households is hit by a negative income shock and receives θw , with $0 < \theta < 1$. Households that receive θw are unable to repay B:

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

Thus, households hit by negative shocks default. In this case, a lender may partially recover the amount due by liquidating the house at the equilibrium price p to be derived below.[4]

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 liquidates the defaulting mortgage:

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

A.2 Equilibrium housing prices, banks' contracts, and strategic defaults

In absence of shocks, households demand housing if:

$$\gamma_i \geq p.$$

Since γ_i is uniformly distributed, the equilibrium price is determined by equating aggregate demand and supply:

[4] This assumption puts an upper bound on households' indebtness: $B < p$, where p is the equilibrium price prevailing when no negative shock occurs. If the repayment obligation were larger than the equilibrium price prevailing when no negative shocks occur, households would always default as they have the option to surrender the house to the bank.

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

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

In contrast, when households are hit by a negative income shock, they cannot repay B (by (1)). If lenders seize their houses, a fraction e of households become financially constrained and cannot participate in 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 some households with high housing utility cannot participate in the market. As the aggregate demand is lower, the house price has to fall in order to clear the market.

An equilibrium in which lenders liquidate the houses of defaulting borrowers implies that $p^L < B$; otherwise the households hit by negative shocks would prefer to sell their houses and pay back the mortgage. This implies that in an equilibrium with liquidation, households with a high income realization always strategically default because they can purchase a house at a price lower than B. In this equilibrium with liquidation and strategic defaults, the following condition always holds:[5]

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

[5] This is the only equilibrium with liquidation (and strategic defaults). The condition $p^L < w$ 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 shock occurs would want and would be able to purchase a house, driving the equilibrium house price above θw.

meaning that households that suffer a negative shock are unable to participate in the housing market (the first inequality), while non-distressed households default strategically.[6] The above discussion can be summarized in the following Lemma.

Lemma 1 *If defaulting loans are liquidated, the equilibrium price drops, and unaffected borrowers find it optimal to default strategically.*

A.3 Renegotiation

If, instead of liquidating defaulting mortgages, lenders were to renegotiate their loans accepting a lower loan repayment, households would remain in possession of their houses. Aggregate housing demand would remain the same as in absence of shocks, and the equilibrium price under renegotiation p^R would be:

$$p^R = p = \overline{\gamma} - \overline{H}.$$

In this equilibrium with renegotiation, unaffected households would have no incentive to default strategically. However, since $\theta w < \overline{\gamma} - \frac{\overline{H}}{1-e} = p^L$, the housing price under liquidation is always larger than the highest payment θw a lender can obtain if it were to renegotiate with a distressed borrower, protected by limited liability. It follows that for an atomistic lender it is always optimal to liquidate rather than renegotiate defaulting loans.

Proposition 1 *Atomistic lenders never renegotiate with defaulting households.*

A.4 Banking concentration, house prices and strategic defaults

We now consider the case in which one mortgage lender holds a large fraction ξ of the outstanding mortgages (henceforth, large lender). This large lender internalizes that its decision to renegotiate has an effect on the aggregate demand for housing.

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

When the large bank renegotiates, its borrowers will continue to participate in the housing market. Under the assumption that atomistic lenders continue to liquidate (which will be verified in equilibrium), the aggregate housing demand is:

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

and the equilibrium price is:

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

which is larger than p^L. Furthermore, $p^{L'}$ increases in ξ , the parameter capturing outstanding mortgage concentration.

For values of ξ sufficiently close to 1, the equilibrium price could be such that $p^{L'} > B$. No (strategic or liquidity) defaults would occur in this case: those households hit by the negative shock that are also client of the large lender would enjoy a debt write down; the remaining households experiencing a negative income shock would sell their house and repay the mortgage.

For smaller values of ξ , the house price may fall below B and any borrower, including those of the large lender that have not suffered a negative income shock would want to default. Under the assumption that lenders can distinguish between households that have and have not been hit by the shock, the large bank can offer to write down the mortgages of non-distressed households to $B' = p^{L'}$, and these households would find it optimal to accept the offer.

The assumption that at least the large lender can distinguish between households that suffer a negative income shocks and households that do not is crucial. If this was not possible, intact households could strategically ask for a loan modification. Here, we make the assumption that income shocks are observable even though not verifiable.[7] This assumption is based on the idea that lenders have access to a wealth of information on their borrowers and should therefore be able to identify pools of borrowers particularly likely to be in economic distress (see Ghent (2011) for

[7] The model could be extended to allow banks to imperfectly distinguish between intact and distressed households.

some evidence).[8]

Under this assumption, when a fraction e of households suffer a negative income shock, the large lender is willing to renegotiate, rather than liquidate, defaulting loans 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 be satisfied as ξ increases.

Also, if this condition holds, not only the impact of the negative income shocks on house prices is smaller, but also aggregate mortgage losses fall. The reason is that all lenders, and not only the one with a large fraction of outstanding mortgages, obtain a higher average repayment. In fact, atomistic lenders are able to liquidate the houses of defaulting borrowers at a higher price. As a result, a smaller fraction of the outstanding mortgages is written down by both large and atomistic lenders.

It is worth noticing that under the assumptions made so far, when a large lender renegotiates its defaulting loans, the other lenders have even stronger incentives to liquidate as the equilibrium house price is higher. Thus, a large lender alone cannot prevent foreclosures and strategic defaults, but it can mitigate the effects of negative income shocks on house prices.[9] The following proposition summarizes this discussion.

Proposition 2 *Ceteris paribus, the higher is the concentration of the outstanding mortgages, the smaller are the effects of negative income shocks on house prices.*

[8] It is also relevant to note –even though it remains outside our model– that in concentrated mortgage markets, lenders are also likely to have soft information about the borrowers that would help in the decision whether to modify the mortgage. This would reinforce the results we present hereafter.

[9] If we introduced a cost of default for households, the model would imply that lending concentration reduces defaults to a larger extent further mitigating the effects of negative shocks on house prices.

The main prediction of the model is that mortgage lending concentration mitigates the effect of negative income shocks on house prices by reducing lenders' propensity to foreclose defaulting borrowers. In the next section, we design an empirical strategy to test this prediction, and investigate the mechanisms linking mortgage concentration to the changes in house prices and foreclosures.

III Empirical Evidence

A Empirical Design

The model suggests that a negative shock may be amplified by lenders' liquidation decisions in geographical areas with dispersed mortgage lending. The effect arises because of a pecuniary externality of foreclosures, which existing literature documents to operate within narrowly defined geographical areas, such as zip codes (see Campbell, Giglio and Pathak, 2011; Mian Sufi and Trebbi, 2013, Anenberg and Kung, 2013).

As illustrated by our stylized model, the pecuniary externality may operate through strategic defaults that amplify the effect of negative shocks on house prices. Although the notion that price drops and liquidity defaults 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 effect of negative shocks on house prices even if the pecuniary externality operated through a different mechanism. For instance, a given income shock may be amplified if households with foreclosed homes are forced to move out of their neighborhood thus decreasing the income of local retailers who may in turn default on their own mortgages. Lenders with a large exposure to a geographical area may be able to internalize these effects and avoid foreclosures.

Since the intensity of the shock may endogenously depend on these feedback effects, it is important to isolate exogenous income shocks. We achieve this in two ways. First, we build on Bartik (1991) and use employment levels in one-digit SIC industries in a given geographical area (e.g., MSA) and national growth rates of earnings in each industry to predict local income shocks. That is, we predict expected income growth in a geographical area between periods t and $t+k$ based on the industry mix in that geographical area at time t and the change in industry earnings for the entire U.S. between t and $t+k$. This way of measuring local income shocks has been widely used in the literature (see, for instance, Blanchard and Katz, 1992; Saiz, 2010; Guerrieri, Hartley and Hurst, 2013) and is less sensitive than actual income growth to feedback effects as the ones described above.

Second, while the externalities due to foreclosures are expected to be stronger within limited geographical areas, such as the zip codes, income shocks are likely to affect larger geographical areas because households typically commute to jobs within MSAs. For this reason, we compute our measure of income shock at the MSA level, and perform our analysis within areas that are likely to experience common shocks (such as MSAs or counties). Thus, we ask whether within an MSA (or a county) affected by the same economic shock, zip codes with higher concentration of outstanding mortgages experience smaller house price depreciations and fewer foreclosures, as our model predicts.

Since our theory has predictions for negative income shocks only and we keep the intensity of the shock constant in our within-county (or within-MSA) analysis, we measure negative income shocks with a dummy variable that takes a value equal to 1 if the predicted expected income growth using the Bartik methodology is negative, and zero otherwise.

B Data sources

We combine a variety of data sources. To measure mortgage lending concentration and other characteristics of the local housing market, we use data from the Home Mortgage Disclosure Act (HMDA). The Home Mortgage Disclosure Act requires depository and non-depository financial institutions with assets above an annually adjusted threshold to report information on mortgage applications, the loan disposition, including whether it is retained or securitized, and other mortgage characteristics that can be used to track lending trends (see, e.g., Mian and Sufi, 2009; Glaeser, Gottlieb and Gyourko, 2010; Favara and Imbs, 2011, Loutskina and Strahan, 2011). HMDA is a comprehensive source of information on primary U.S. mortgage originations, covering over 90 percent of the mortgage activity of commercial banks, thrifts, credit unions, and mortgage companies. Since HMDA does not report zip codes, for each lender, we aggregate HMDA data up to the census tract level and match census tracts to ZIP codes using Census Tract Crosswalks, a match provided by Population Studies Center.

We obtain foreclosure data on residential properties from RealtyTrac.com, one of the leading online marketplace for foreclosure properties, covering over 92 percent of housing units in the U.S.. RealtyTrac.com collects information on distressed properties from the moment a borrower defaults on payments, and a lender files a notice of default, to the moment a lender submits a notice of sale, and the property is sold at a public action. Using information on the location of a distressed property, we keep track of the number of foreclosure auctions and construct a zip code level measure of forced sales.

As banks' propensity to foreclose or renegotiate mortgages in default may also depend on the mortgage law prevailing in the state where they operate, we gather information on bankruptcy procedures from Rao and Walsh (2009). This information is used to classify states depending on whether lenders must receive a judge's approval to foreclose (judicial foreclosure states). From Cutts and Merrill (2008), we also obtain information on the estimated number of days required to accomplish a foreclosure, another proxy for the overall cost of a foreclosure procedure.

Data on house prices at the zip code level are from CoreLogic that provides quality-adjusted house price indexes for existing single-family properties.We exclude zip codes in HMDA or RealtyTrack.com that have no match with Corelogic. We supplement these data with zip code level annual data for outstanding credit and mortgage delinquency rates from Equifax.

Finally, we control for local economic, financial and housing conditions using other data sources. Zip code level information on income per capita and population comes from the Bureau of Census. Industry income and employment at the MSA level are from the Bureau of Economic Analysis.

All data are collected at annual frequency from 2001 to 2009 and, to smooth out year-on-year fluctuations, collapsed into three subperiods, 2001-2003, 2004-2006 and 2007-2009, covering the recent boom and bust in the U.S. housing market.

C Measuring the concentration of outstanding mortgages

Our measure of outstanding mortgage concentration is based on the model's prediction that concentration matters not for its ex ante effects on contract terms, but for the way in which it affects lenders' ex-post incentives to foreclose properties. Accordingly, we construct a proxy for concentration that measures a lender's exposure to the local mortgage market.

We aggregate HMDA data at the zip code level keeping track of the number and the dollar amount of conventional loans originated for the purchase of single-family, owner-occupied houses, as well as of securitized loans.[10] We then compute for each zip code an Herfindahl index with market shares defined as the volume of mortgage loans originated and retained by individual lenders in any 3-year period relative to the total volume of loans originated in the same zip code over the same period. We choose a 3-year window because we want to measure concentration in terms of the stock (not the flow) of retained mortgages.

Importantly, we assign to each lender only mortgages retained, because losses associated to the default of securitized mortgages are unlikely to be borne by the original lender. Thus, while the denominator of each lender's share in the local mortgage market includes both retained and securitized mortgages, the numerator includes only retained loans.[11]

We classify a mortgage as securitized, if it is 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; mortgages issued at the end of the year may be securitized at the beginning of the following year and thus improperly classified

[10] We exclude loans for the purchase of multi-family dwellings, second and vacation homes because we observe only house prices indexes for single-family owner-occupied houses. We also exclude loans for refinancing and home improvement.

[11] Since independent mortgage lenders securitize virtually all their mortgages, the numerator considers only retained mortgages by commercial banks, while the denominator includes all mortgages originated in a zip code over a three-year period.

as retained.[12]

To avoid simultaneity problems, we use indexes of outstanding mortgages concentration computed over the period $(t, t+2)$ to explain the change in house prices during the interval $(t+3, t+5)$.[13] In practice, we explore how our index of outstanding mortgage concentration in 2001-2003 and 2004-2006 explains changes in house prices in 2004-2006 and 2007-2009. We do so to minimize concerns that housing market developments affect the concentration of outstanding mortgages, even though this reverse causality argument is not a big concern in our analysis. If concentration were driven by house price changes, large shocks would be more likely to wipe out smaller lenders, increasing concentration and introducing a downward bias in the estimates of the outstanding mortgage concentration coefficient.

D Descriptive statistics

Our sample consists of maximum of 6,320 zip codes in 200 urban counties of 84 MSAs in continental U.S., for which zip code level price indexes and mortgage data are available. As common in the literature, we focus on urban areas because house price dynamics, borrower characteristics, and mortgage lending decisions have different determinants in rural, often poor, areas.

Table 1 reports summary statistics together with variable definitions and data sources. On average, outstanding mortgages in our sample are very dispersed. While the indexes vary little over time, there is substantial cross-sectional variation in the concentration of outstanding mortgages: in some zip codes, the concentration index takes value of zero indicating that all outstanding mortgages have been securitized (or, equivalently, that markets are covered by atomistic lenders); in others zip codes, the concentration index is close to 30 percent, indicating substantial concentration. It is

[12] None of our results changes if we compute market shares based on the number (instead of the volume) of loans originated and retained or if we include the loans originated in the last quarter in the computation of the market shares. 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 always higher than 85%.

[13] The results are invariant if we compute the indexes of outstanding mortgages over the same period as the house price changes.

precisely this large cross-sectional heterogeneity that we exploit in our analysis.[14]

During the period under consideration, a large fraction of loans, 60 percent on average, were securitized, either with GSEs or private institutions, introducing some differences between our two indexes of market concentration. In particular, since independent mortgage lenders securitized all mortgage they issued, when we consider only commercial banks to compute the index of outstanding mortgage concentration, the average concentration of outstanding mortgages is naturally higher. Our different measures of market concentration are, however, highly correlated, with a correlation coefficient larger than 40 percent.

Between 2004 and 2009, house prices experienced a pronounced boom and bust cycle. On average, however, prices decreased by almost 7 percent, reflecting the generalized house price decline in the 2007-2009 period. The observed variation in house prices is also quite heterogeneous, with very few zip codes experiencing price appreciation even in the second subperiod. This partially reflects the fact that even during the 2007-2009 subperiod only 60 percent of the zip codes experienced a negative income shock, defined using the Bartik methodology.

Table 1 also reports summary statistics for the number of foreclosures of single-family properties. Even though a foreclosure process starts when a lender files a default notice (through a notice of default or a lis pendens), we compute the number of foreclosures using only RealtyTrac.com's records for properties that either receive a notice of sale (NOS) or a notice of trustee sale (NTS) and for real estate owned (REO) properties, i.e., properties that have been repossessed by lenders after a notice of default. We follow this strategy because a notice of default may not necessarily lead to a forced sale, given that a defaulting borrower can always reinstate loan payments during a grace period that varies from state to state. As RealtyTrac.com provides reliable data on foreclosure from 2006, we are able to compute average yearly foreclosures only for the subperiod 2007-2009. As shown in Table 1, there is large variation in the number of foreclosures.

[14] In contrast, the time-series variation in the index of outstanding mortgage concentration is more limited.

IV Main results

The main prediction of the model is that income shocks have a muted effect on house prices in areas with higher outstanding mortgage concentration. To test this prediction, we estimate variations of the following reduced form regression:

$$\begin{aligned}\Delta \ln p_{z,i,t} &= \alpha_1 HHI_{z,i,t-1} + \alpha_2 \mathbf{1}_{\Delta \ln y_{i,t}<0} + \alpha_3 HHI_{z,i,t-1} \times \mathbf{1}_{\Delta \ln y_{i,t}<0} \\ &\quad + \beta X_{z,i,t} + \delta_{County,t} + \epsilon_{z,i,t},\end{aligned} \tag{3}$$

where z is an index for zip codes belonging to MSA i, and t an index for the subperiods, i.e. $t = 2004-2006$, and $2007-2009$. The dependent variable, $\Delta \ln p_{z,i,t}$, is the log change of house prices in each subperiod, $HHI_{z,i,t-1}$ the index of mortgage concentration, $\mathbf{1}_{\Delta \ln y_{i,t}<0}$ is an indicator variable equal to one if the MSA i to which a zip code belongs experiences a negative income shock during period t,[15] and $X_{z,i,t}$ summarizes time-varying zip code or county specific controls, accounting for differences in housing and economic conditions. These include the beginning of subperiod- t zip-code income per capita, lagged house prices, and population. Most of these and other control variables we include in our tests are predetermined, but none are truly exogenous. Their inclusion is only an attempt to ensure that our proxies for lending concentration have explanatory power, correcting for the usual house price determinants.

Crucially, we include interactions of county and time fixed effects, $\delta_{County,t}$, to partial out factors common to all zip codes in a county in each subperiod**.** We also explore the robustness of our results to the inclusion of more limited sets of fixed effects, such as interactions of MSA and time fixed effects. The extent to which our estimates vary across these specifications allows us to evaluate whether unobserved factors correlated with time-varying county (or MSA) characteristics may bias our findings. We cluster errors at the county-code level.[16]

[15] Specifically, $\mathbf{1}_{\Delta \ln y_{i,t}<0}$ is equal to one if the income growth in a geographical area, predicted using the Bartik methodology, is negative during period t, and zero otherwise.

[16] The statistical significance of the estimates remains unaffected if we cluster at the MSA level.

The null hypothesis is that $\alpha_2 < 0$ and $\alpha_3 > 0$, meaning that a negative income shock causes house prices to decline for all zip codes within the same MSA, but this drop is less pronounced in zip codes with higher outstanding mortgage concentration. Since the interaction term is constructed using a continuous measure of lending concentration, the coefficient estimate provides a tight link between cross-sectional variation in lending concentration and our model's comparative static results.

The results in Table 3 provide clear support for this prediction. In the first column, the coefficient on the income shock is negative and the interaction term is always positive. The estimates are largely unchanged when we include interactions of MSA and time fixed effects (column 2), interactions of county and time fixed effects (column 3), and interactions of county and zip code time-varying covariates with time effects (column 4). The robustness of the results suggests that our main findings are unlikely to be driven by unobservable local housing, economic, or credit market conditions.

The effect is also significant from an economic point of view. In column 1, the point estimate of α_2 implies that after a negative income shock, house prices drop by 10 percentage points in perfectly competitive lending markets (i.e., for $HHI = 0$), but by only 4 percentage points if the HHI increases by one standard deviation (0.005).

Finally, it is important to note that only in counties experiencing a negative income shock, mortgage lending concentration appears to be positively related to the change in house prices. The coefficient of the outstanding mortgage concentration is, instead, not statistically significant.

A Evaluating alternative explanations

A.1 Are zip codes with higher outstanding mortgage concentration different?

Zip codes with higher outstanding mortgage concentration may differ along a number of other dimensions that could drive our findings. Economic forces leading to aggregate changes in the demand and supply for housing are most likely to operate at the county or even the MSA level.

Therefore, the within-county (or within-MSA) specifications should already control for these factors.

Nevertheless, in Table 3, we take into account specific mechanisms that may be particularly relevant in the context of the housing markets and for smaller geographical units such as zip codes. For instance, borrower average creditworthiness may differ across zip codes within a county. In column 1, we start by including additional controls for the average FICO score, the percentage of subprime borrowers, and the 60 days delinquency rate during the period. Not only the coefficient of our main variable on interest remains invariant, but also the additional controls do not appear to be statistically significant, suggesting that the more parsimonious specifications were already capturing borrower heterogeneity.

Another concern is that outstanding mortgage concentration is correlated with ex ante concentration in mortgage origination. The latter may affect competition and ex ante contract characteristics (Scharfstein and Sunderam, 2013). However, the fact that our results hold within counties should once again mitigate this concern, because borrowers can approach lenders in broader geographical areas, and competition is likely to operate in areas larger than zip codes. Such an interpretation is supported by the estimates in column 2, where controls for ex ante mortgage characteristics, such as the average loan-to-value ratio and the value of mortgages per capita in the zip code, leave our main finding unaffected.[17]

A.2 Securitization and informed lending

One additional concern is that lenders may not renegotiate securitized mortgages for channels alternative to the one suggested by our model. For instance, securitized loans are managed by third-party mortgage servicers and thus likely to be serviced differently from those kept on the balance sheet of the originating institution.[18] As argued by Piskorski, Seru, Vig (2010) and Agarwal

[17] In unreported results, the main estimates are unaffected if we also control for the proportion of deposits held by the top 3 banks in the zip code, a common measure of bank competition, generally computed at the MSA or county level.

[18] Mortgage servicers are not only responsible for collecting payments from mortgage borrowers, but also for handling defaulted loans, including prosecuting foreclosures.

et al, (2011), dispersed ownership and agency problems brought about by securitization could impair mortgage servicers' ex post ability to renegotiate mortgage contracts because of coordination problems.

To address this concern, in column 3 of Table 3, we control for the securitization rate, defined as the period-t zip code average fraction of loans originated and then securitized, and the interaction of the securitization rate with our proxy for the negative income shock. House prices appear to have increased to a larger extent in zip codes with more securitized mortgages, but our measure of outstanding mortgage concentration continues to mitigate the effect of negative income shocks on house price. This appears to be the case also in column 4, when we consider also in the denominator of the market shares only loans issued by commercial banks, which differently from independent mortgage lenders did not automatically securitized all mortgages.

Another possible concern is that in zip codes with high outstanding mortgage concentration, lenders had invested more in information collection and granted mortgages to better borrowers. For instance, Loutskina and Strahan (2011) show that the extent to which a lender's mortgage portfolio is diversified across MSAs is inversely correlated with the lender's investment in private information. The concentration of the outstanding mortgages in a zip code and the average portfolio diversification of the lenders in a zip code could be correlated in a way that drives our results. To evaluate the merit of this alternative explanation, we compute the portfolio diversification of each lender in our sample, as Loutskina and Strahan (2011) do, and then compute an average portfolio diversification for all lenders in a zip code. In column 1 of Table 4, we control for the average bank diversification in the zip code and the interaction of the latter with the dummy capturing the negative income shock. We find that the effect of the outstanding mortgage concentration is unaffected suggesting that private information is unlikely to drive our main findings.

The lending technology and its reliance on private, especially soft, information is often believed to be related to the size of the lender (Berger, Miller, Petersen, Rajan, and Stein, 2005). If zip codes with small lenders were to have higher outstanding mortgage concentration, the soft information of these lenders, rather than their ex post incentives due to their share of outstanding mortgages, may allow them to renegotiate or may even improve their ex ante lending decisions. For this reason, we include, along with our index of outstanding mortgage concentration, an index in which we compute the market shares of mortgages retained by commercial banks which are in the lowest quartile of the lenders' distribution by asset size. We would expect the interaction of the latter with the negative income shock to capture most of the effect of the outstanding mortgage concentration if the banks' organizational structure and soft information matter. In column 2, we find no evidence that this is the case. Results are equally invariant if we control for salient local banks' characteristics, such as average bank size, profitability and capitalization in the zip code (column 3).

Overall, these findings do not support the hypothesis that in zip codes with higher concentration of outstanding mortgages, lenders may have selected more creditworthy borrowers. Such an interpretation is also consistent with the earlier result in column 1 of Table 3, where the effect of outstanding mortgage concentration is unaffected when we control for borrowers ex post performance.

B Mortgage concentration and judicial foreclosure

To sharpen the interpretation of our findings, we test further cross-sectional implications of our theory. According to the model, lenders with larger shares of outstanding mortgages internalize to a larger extent the effects of foreclosures on house prices. A corollary of this prediction is that outstanding mortgage concentration should have a smaller effect on house prices in areas where foreclosures are less likely. To evaluate this additional prediction, we study the differential effect of outstanding mortgage concentration on house prices in zip codes with different foreclosure procedures. In the U.S., 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 in Pence (2006), the first procedure imposes on lenders more costs and more lengthy foreclosure timelines. Accordingly, lenders' incentives to foreclose are weaker in judicial foreclosure states regardless of their exposure to mortgage losses. Mian, Sufi and Trebbi (2012) provide supportive evidence for this prediction during the recent U.S.

housing market collapse. Building on this evidence, we expect a stronger effect of outstanding mortgage concentration on house prices following negative shocks in the subsample of zip codes located in non-judicial foreclosure states.

Since the number of days it takes to seize a property from a delinquent borrower also significantly increases the cost of foreclosure in a state, we also expect our results to be stronger in the subsample of zipcodes in states with an average length of time required to accomplish a foreclosure below the cross-sectional median.

Table 5 presents the estimates of equation (3) in subsamples of zip codes with high and low costs of foreclosures, respectively. It appears that the mitigating effect of outstanding mortgage concentration on negative shocks is smaller and not statistically different from zero in the subsamples of zip codes with higher cost of foreclosure (columns 2 and 4). The difference in the coefficients of the interaction terms of interest in columns 1 and 2 is statistically significant at 1 percent level, while it is not statistically significant at conventional levels in columns 3 and 4. This is largely unsurprising as the sample split based on judicial and non-judicial foreclosure states relies on sharper differences than the second sample split based on the duration of the judicial foreclosure process.

C Foreclosures and mortgage concentration

The mechanism outlined in our model suggests that mortgage concentration mitigates the effects of negative shocks on house prices because it limits a lender's propensity to foreclose defaulting loans, not because there are fewer defaults in these zip codes. In this subsection, we test the validity of this mechanism using delinquency and foreclosure data. As we do not observe foreclosures in the period preceding the financial crisis, we rely on cross-sectional variation across U.S. zip codes during the 2007-2009 period.

The regression analysis is therefore based on the following equation:

$$
\begin{aligned}
y_{z,i,t} = & \alpha_1 HHI_{z,i,t-1} + \alpha_2 \mathbf{1}_{\Delta \ln y_{i,t}<0} + \alpha_3 HHI_{z,i,t-1} \times \mathbf{1}_{\Delta \ln y_{i,t}<0} \\
& + \beta X_{z,i,t} + \delta_{County,t} + \epsilon_{z,i,t},
\end{aligned}
$$

where the dependent variable is in turn either the number of delinquencies or the number of foreclosures. The set of controls include proxies for the size of the zip code, such as the total population.

We start by verifying our earlier conclusion that lenders did not issue mortgages to more creditworthy borrowers in zip codes with higher outstanding mortgage concentration. Lenders with private information would be expected to extend mortgages to borrowers that are less likely to default ex post if negative shocks occur. The estimates in column 1 of Table 6 show that our proxy for outstanding mortgage concentration is unrelated to the number of 60 days delinquencies in the zip code.

We then move to test the mechanism underlying our theory that outstanding mortgage concentration reduces the number of foreclosures. The estimates in column 2 to 5 of Table 6 fully support this prediction. Importantly, outstanding mortgage concentration does not consistently reduce foreclosures in zip codes that did not experience negative shocks.

The effects are also economically significant. After a negative income shock, a zip code with an average outstanding mortgage concentration experiences 35 percent fewer foreclosures than a zip code in which the outstanding mortgages are held by atomistic lenders.[19] The magnitude and the statistical significance of the estimated coefficients do not change if we include MSA orcounty fixed effects. Results are also invariant in column 5, when we control for the extent of securitization, FICO score, and other mortgage characteristics.

Finally, in Table 7, we exploit state level differences in foreclosure costs. As argued above,

[19] The economic effect is computed by noting that the parameter estimates imply that there are on average 40 more foreclosures in a zip code in which outstanding mortgages are dispersed across atomistic lenders, but only 35 in zip codes with a one-standard deviation higher outstanding mortgage concentration.

lenders have stronger incentives to foreclose if the process does not require a judicial intervention. In these areas, lenders' decisions to foreclose are expected to be influenced by their share of outstanding mortgages to a larger extent. Our estimates support this prediction. In zip codes hit by a negative income shock, foreclosures increase less when outstanding mortgages are highly concentrated, but the effect of concentration is attenuated in jurisdictions with costly foreclosure procedures, where all lenders are less likely to foreclose, independently from their share of outstanding mortgages. The differences in the coefficients of the interaction terms of interest between columns 1 and 2 and columns 3 and 4, respectively, are statistically significant at 1 percent level, fully supporting the mechanism of our theory.

V 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 micro-evidence supporting this mechanism using cross-sectional differences in housing price depreciation and concentration of outstanding mortgages across U.S. zip codes during the recent housing market collapse. We find that following negative shocks, house prices drop to a lower extent in markets with higher outstanding mortgage concentration. Moreover, markets with high outstanding mortgage concentration experience fewer foreclosures.

These findings have important policy implications. In taking foreclosure decisions, lenders are affected by the outstanding mortgages on their balance sheets. When income 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. This in turn mitigates the effects of negative shocks on house prices. Similar effects may be achieved with the creation of bad banks that collect impaired loans at times of crises.

Our findings can also explain why banks may be offering refinancing at time of crisis. Our model would predict that banks are more likely to do so in neighborhoods in which they have a high share of the outstanding mortgages in order to limit the negative externalities due to foreclosures.

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 the pecuniary externality can be internalized by lenders with a high share of the outstanding claims is an exciting venue for future research.

References

Adelino, M., K. Gerardi, and P. S. Willen. 2010a. What Explains Differences in Foreclosure Rates? A Response to Piskorski, Seru, and Vig. Working Paper 10-2, Federal Reserve Bank of Boston.

Adelino, M., K. Gerardi, and P. S. Willen. 2010b. Why Don't Lenders Renegotiate More Home Mortgages? The Effect of Securitization. Working Paper 2009-17a, Federal Reserve Bank of Atlanta.

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.

Anenberg, E., and E. Kung, 2013. Estimates of the Size and Source of Price Declines due to Nearby Foreclosures, Finance and Economics Discussion Series 2012-84. Board of Governors of the Federal Reserve System.

Bartik, T.J., 1991. Who Benefits from State and Local Economic Development Policies? W.E. Upjohn Institute for Employment Research, Kalamazoo, Mich.

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.

Black, S. E., and P. E. Strahan, 2002. Entrepreneurship and bank credit availability, *Journal of Finance* 57, 2807-2834.

Blanchard, O.J. and L. F. Katz, 1992. Regional evolutions. *Brookings Papers on Economic Activity*, 1–75.

Campbell, J. Y., S. Giglio, and P. Pathak, 2011. Forced sales and house prices, *American Economic Review* 101, 2108-2131.

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.

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

Favara, G. and J. Imbs, 2010. Credit Supply and the Price of Housing, Working Paper, Board of Governors of the Federal Reserve System.

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.

Gerardi, K. L., Lambie-Hanson, L., and Willen, P. S., 2011. Do Borrower Rights Improve Borrower Outcomes? Evidence from the Mortgage Market, Working Paper, Federal Reserve Bank of Atlanta.

Ghent, A. C., 2011. Securitization and Mortgage Renegotiation: Evidence from the

Great Depression, *Review of Financial Studies* 24, 1814–1847.

Glaeser, E., J. D. Gottlieb and J. Gyourko, 2010. Can Cheap Credit Explain the Housing Boom?, Working Paper, Harvard University.

Guerrieri, V., D. Hartley, and E. Hurst, 2013. Endogenous gentrification and housing price dynamics, *Journal of Public Economics* 100, 45–60.

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

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

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.

Keys, B. J., A. Seru, and V. Vig, 2012. Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets, *Review of Financial Studies* 25, 2071–2108.

Loutskina, E., and P. E. Strahan, P. E., 2011. Informed and uninformed investment in housing: The downside of diversification, *Review of Financial Studies* 24, 1447–1480.

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.

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

Mian, A., A. Sufi, and F. Trebbi, 2012. Foreclosures, House Prices, and the Real Economy, mimeo University of Chicago.

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.

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

Shleifer, A., and R. Vishny, 2010. Fire Sales in Finance and Macroeconomics, *Journal of Economic Perspectives* 25, 29-48.

Table 1
Variables' Description and Data Sources

Variable Name	Variable Description	Source	mean	p10	p90	sd	Obs.
60 Days Delinquency Rate	Zip code proportion of the outstanding mortgages that is between 60 and 89 days delinquent	Equifax	0.0101	0.0013	0.0226	0.0193	12905
Bank Capital	Average bank equity capital ratio in a zip code	Call Report	0.0996	0.0836	0.1189	0.0172	12184
Bank ROA	Average bank return on asset in a zip code	Call Report	0.0326	0.0286	0.0369	0.0059	12184
Bank Size	Average bank log asset in a zip code	Call Report	18.8067	16.5925	20.4473	1.8133	12184
Lender Diversification	Zip code average of the lender diversification index, defined as the sum of squared shares for mortgage volume originated by each lender in each MSAs in which it operates relative to the total volume of loans originated by same lender. Lenders include commercial banks, thrifts, credit unions and mortgage companies.	HMDA	0.0850	0.0155	0.1864	0.0765	12936
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)	0.5131	0.0000	1.0000	0.4998	12936
FICO score	Average risk core in a zip code (divided by 100)	Equifax	6.9384	6.4561	7.3779	0.3557	12907
Foreclosures	The zip code's yearly number of foreclosures, defined as the sum of notices of trustee sale, notice of sales, and real estate owned (REO) properties (divided by 100).	RealtyTrac.com	0.8528	0.0700	1.9967	0.7279	6429

Continues

Table 1 (continued)

Variable Name	Variable Description	Source	mean	p10	p90	sd	Obs.
Lagged HHI	Sum of squared shares of the mortgage loans retained in the balance sheet of commercial bank lenders in a zip code. The shares are based on the volume of loans originated and retained by a commercial bank in a zip code relative to the total volume of loans originated by all lenders in the same zip code. Unless otherwise noted in the text, loans (originated and/or retained) are measured over a three-year period preceding the one in which the dependent variables are defined. Loans are conventional mortgages for purchase of single-family owner-occupied houses. Lenders include commercial banks, thrifts, credit unions and mortgage companies.	HMDA	0.0030	0.0007	0.0060	0.0050	12936
Lagged HHI-Banks	Defined as Laggerd HHI, but considering only the volume of loans originated and retained in a zip code by commercial banks to compute the denominator of the shares.	HMDA	0.0222	0.0049	0.0468	0.0243	12934
Lagged HHI-Small Banks	Defined as Laggerd HHI-Banks, but considering only the volume of loans originated and retained in a zip code by small commercial banks, definied as banks in the lowest quartile of the distrubtion by asset size.	HMDA	0.0052	0.0002	0.0122	0.0121	12934
House price growth	Logarithmic change of the zip code house price index for single-family owner-occupied houses.	CoreLogic	-0.0670	-0.4060	0.2413	0.2442	12638
HPI	Logarithm of the real zip code house price index for single-family owner-occupied houses.	CoreLogic	4.3793	4.0818	4.7189	0.2477	12638

Continues

Table 1 (continued)

Variable Name	Variable Description	Source	mean	p10	p90	sd	Obs.
Judicial Foreclosure	Dummy variable that takes value 1 for zip codes in states with a judicial requirement for foreclosure	Rao and Walch (2009)	0.5434	0.0000	1.0000	0.4981	12936
LTV ratio	Average loan to value ratio in a zip code	Lender Processing Servicer (LPS)	0.7819	0.7075	0.8521	0.0704	12437
Median Income	Logarithmic median income in the zip code	U.S. Census Bureau	10.9517	10.5522	11.3633	0.3228	12936
Mortgage per capita	The zip code's number of first mortgages and home equity lines outstanding divided by the number of households (/ by 100,000)	Equifax	0.7518	0.2845	1.3612	0.4781	12905
Negative Shock	Dummy variable that takes value equal to 1 if the Bartik index predicts negative income growth in the MSA during the time period	U.S. Census Bureau	0.2892	0.0000	1.0000	0.4534	12936
Population	Logarithmic zip code's population	U.S. Census Bureau	8.5663	8.1789	8.9666	0.3550	12936
Securitized Loans	The zip code's fraction of loans originated for purchase of single family owner occupied houses sold within the year of origination to other non-affiliated financial institutions or government-sponsored housing enterprises.	HMDA	0.6490	0.5346	0.7487	0.0874	12936
% Subprime Borrowers	Fraction of households in a zipcode with FICO score below 620	Equifax	0.2566	0.1108	0.4263	0.1247	12907

Table 2
Changes in House Prices and Mortgage Concentration

Zip code level pooled regressions of the log change in house prices on the lagged Herfindahl index and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. All variable definitions and sources are reported in Table 1. All regressions include a time dummy for the period 2007-2009, a constant and other fixed effects as indicated in the table, whose coefficients we do not report. 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)
Negative Shock	-0.096***			
	(0.021)			
Lagged HHI×Negative Shock	5.826**	4.404***	3.744***	2.963***
	(2.642)	(0.867)	(1.052)	(0.841)
Lagged HHI	-0.605	0.105	0.073	0.128
	(0.643)	(0.220)	(0.133)	(0.119)
Lag HPI	-0.120***	-0.036**	-0.010	0.004
	(0.023)	(0.015)	(0.011)	(0.013)
Population	0.004	-0.006**	-0.007***	-0.004
	(0.008)	(0.002)	(0.002)	(0.003)
Income	0.315	0.604***	0.619***	-0.076
	(0.303)	(0.203)	(0.177)	(0.300)
Lag HPI×Negative Shock				-0.035
				(0.031)
Population×Negative Shock				-0.008
				(0.006)
Income×Negative Shock				2.403***
				(0.502)
Obs	12638	12638	12638	12638
FE	Time	MSA×Time	County×Time	County×Time
N-Clust	684	684	684	684
Adjusted R squared	0.63	0.94	0.96	0.96

Table 3
Are Zip Codes with Higher Mortgage Concentration Different?

Zip code level pooled regressions of the log change in house prices on the lagged Herfindahl index and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. All variable definitions and sources are reported in Table 1. All regressions include interactions of time and county dummies and a constant, whose coefficients we do not report. Standard errors in parenthesis are clustered at the county 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)
Lagged HHI×Negative Shock	3.231***	3.562***	4.213***	
	(0.959)	(1.077)	(1.113)	
Lagged HHI	0.045	0.042	0.185*	
	(0.137)	(0.136)	(0.106)	
Lagged HHI-Banks×Negative Shock				0.551***
				(0.212)
Lagged HHI-Banks				0.125***
				(0.045)
Securitized Loans×Negative Shock			-0.022	-0.018
			(0.049)	(0.047)
Securitized Loans			0.115***	0.125***
			(0.031)	(0.034)
% Subprime Borrowers	-0.013			
	(0.038)			
FICO Score	0.019			
	(0.015)			
60 Days Delinquency Rate	-0.234			
	(0.217)			
Mortgage per capita		0.004		
		(0.004)		
LTV Ratio		-0.032***		
		(0.011)		
Lag HPI	-0.012	-0.014	-0.012	-0.013
	(0.011)	(0.012)	(0.012)	(0.012)
Population	-0.009***	-0.006***	-0.009***	-0.008***
	(0.003)	(0.002)	(0.002)	(0.002)
Income	-0.375	0.298	0.666***	0.812***
	(0.236)	(0.186)	(0.149)	(0.140)
Obs	12607	12172	12638	12636
FE	County×Time	County×Time	County×Time	County×Time
N-Clust	684	682	684	684
Adjusted R squared	0.96	0.96	0.96	0.96

Table 4
Does Information Drive the Effect of the Mortgage Concentration?

Zip code pooled regressions of the log change in house prices on the lagged Herfindahl index and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. All variable definitions and sources are reported in Table 1. All regressions include interactions of time and county dummies and a constant, whose coefficients we do not report. 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)
Lagged HHI×Negative Shock	3.659***	3.906***	3.536***
	(1.050)	(1.048)	(1.033)
Lagged HHI	0.070	0.038	0.085
	(0.135)	(0.144)	(0.134)
Lender Diversification×Negative Shock	0.097*		
	(0.055)		
Lender Diversification	0.042*		
	(0.022)		
Lagged HHI-Small Banks×Negative Shock		-0.486**	
		(0.232)	
Lagged HHI-Small Banks		0.143**	
		(0.071)	
Bank Capital			-0.045
			(0.035)
Bank ROA			-0.165
			(0.115)
Bank Size			-0.000
			(0.000)
Lag HPI	-0.012	-0.010	-0.013
	(0.011)	(0.011)	(0.012)
Population	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
Income	0.551***	0.632***	0.684***
	(0.174)	(0.178)	(0.182)
Obs	12638	12636	11922
FE	County×Time	County×Time	County×Time
N-Clust	684	684	682
Adjusted R squared	0.95	0.96	0.96

Table 5
Changes in House Prices, Mortgage Concentration and Judicial Foreclosures

Zip code level pooled regressions of the log change in house prices on the lagged Herfindahl index and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. Column 1 report the estimates for the subsample of zip codes in states that allow non-judicial foreclosure, column 2 for the subsample of zip codes in states that only allow judicial foreclosures; column 3 for the subsample of zip codes in states in which the foreclosure procedure takes a number of days below the median; and column 4 for the subsample of zip codes in states in which the foreclosure procedure takes a number of days above the median. All variable definitions and sources are reported in Table 1. All regressions include interactions of time and county dummies and a constant, whose coefficients we do not report. 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.

	Non Judicial Foreclosures (1)	Judicial Foreclosures (2)	No. Days < Median (3)	No. Days > Median (4)
Lagged HHI×Negative Shock	5.503***	1.233	5.169***	1.373
	(0.901)	(0.775)	(0.818)	(0.880)
Lagged HHI	-0.024	0.144	0.110	-0.159
	(0.196)	(0.136)	(0.142)	(0.284)
Lag HPI	-0.022	0.002	-0.024	0.006
	(0.020)	(0.011)	(0.019)	(0.011)
Population	-0.008**	-0.005**	-0.009**	-0.004**
	(0.004)	(0.002)	(0.004)	(0.002)
Income	0.739**	0.444***	0.775**	0.392**
	(0.336)	(0.157)	(0.321)	(0.158)
Obs	5800	6838	6198	6440
FE	County	County	County	County
N-Clust	322	362	316	368
Adjusted R squared	0.96	0.96	0.95	0.96

Table 6
Foreclosures and Mortgage Concentration

Zip-code level cross sectional regressions of the number of 60 days delinquencies (column 1) and the number of foreclosures (columns 2 to 5) between 2007 and 2009 on the Herfindahl index, and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. All variables and sources are defined in Table 1. All regressions include interactions of time and county dummies and a constant, whose coefficients we do not report. Standard errors in parenthesis are clustered at the county level and corrected for heroskedasticity. Estimates followed by ***, **, and * are statistically different from zero with 0.01, 0.05 and 0.10 significance levels, respectively.

Dependent Variable	60 Days Delinquencies (1)	Number Foreclosures (2)	Number Foreclosures (3)	Number Foreclosures (4)	Number Foreclosures (5)
Negative Shock		0.403***			
		(0.091)			
Lagged HHI×Negative Shock	-4.986	-20.106*	-23.440*	-25.788*	-25.925**
	(3.772)	(10.856)	(12.137)	(13.747)	(11.372)
Lagged HHI	-2.276	0.555	-14.055**	-10.446	-0.935
	(2.847)	(7.817)	(6.519)	(6.957)	(6.517)
Securitized Loans×Negative Shock	-0.015				-0.458
	(0.131)				(0.290)
Securitized Loans	0.361***				0.848***
	(0.100)				(0.234)
FICO Score	-0.521***				-0.975***
	(0.023)				(0.073)
Mortgage per capita	0.064***				0.123***
	(0.016)				(0.036)
LTV Ratio	0.113***				0.191***
	(0.035)				(0.066)
Lag HPI	-0.012	0.394***	0.108	-0.020	0.007
	(0.041)	(0.149)	(0.177)	(0.111)	(0.086)
Population	0.110***	0.165**	0.166***	0.188***	0.129***
	(0.013)	(0.067)	(0.034)	(0.030)	(0.022)
Income	6.993***	-25.112***	-24.831***	-25.567***	7.253***
	(1.248)	(2.721)	(2.042)	(2.099)	(2.157)
Obs	5910	6283	6283	6283	5884
FE	County		MSA	County	County
N-Clust	656	672	672	672	646
Adjusted R squared	0.57	0.13	0.62	0.72	0.78

Table 7
Foreclosures, Mortgage Concentration and Liquidation Costs

Zip code level pooled regressions of the number of foreclosures between 2007 and 2009 on the lagged Herfindahl index and its interaction with the negative shock dummy that equals 1 if the change in the Bartik index of the MSA in which a zip code is located during the period is negative. Column 1 report the estimates for the subsample of zip codes in states that allow non-judicial foreclosure, column 2 for the subsample of zip codes in states that only allow judicial foreclosures; column 3 for the subsample of zip codes in states in which the foreclosure procedure takes a number of days below the median; and column 4 for the subsample of zip codes in states in which the foreclosure procedure takes a number of days above the median. All variable definitions and sources are reported in Table 1. All regressions include interactions of time and county dummies and a constant, whose coefficients we do not report. 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.

	Non Judicial Foreclosures (1)	Judicial Foreclosures (2)	No. Days < Median (3)	No. Days > Median (4)
Lagged HHI×Negative Shock	-43.054***	0.553	-38.016***	-7.758
	(16.568)	(9.027)	(12.918)	(10.261)
Lagged HHI	-17.135	-7.086	-17.361*	2.168
	(14.968)	(6.257)	(9.716)	(9.066)
Lag HPI	-0.018	-0.070	-0.072	0.015
	(0.198)	(0.113)	(0.176)	(0.120)
Population	0.185***	0.198***	0.271***	0.118***
	(0.046)	(0.037)	(0.040)	(0.034)
Income	-21.763***	-28.023***	-23.550***	-27.012***
	(3.069)	(2.601)	(2.737)	(3.040)
Obs	2890	3393	3083	3200
FE	County	County	County	County
N-Clust	319	353	311	361
Adjusted R squared	0.67	0.69	0.66	0.69