Fire-Sale Risk and Credit

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Abstract

This paper examines whether the risk of future collateral fire sales affects lending decisions. We study US mortgage applications and exploit exogenous variation in foreclosure frictions for identification. We find that lenders are less likely to approve mortgages when anticipated losses due to uncoordinated collateral liquidations are high, and when there is elevated risk of joint collateral liquidation. As expected, these results are stronger when fire-sale risk is more salient. The results suggest that fire-sale risk has implications for credit allocation, and that lenders' collective (ex-ante) origination decisions mitigate fire-sale exposures ex-post.

Keywords: fire sales, credit supply, foreclosure laws, creditor concentration, joint liquidation risk, collateral

JEL: G21; G11;
Declarations of interest: none

1 Introduction

Prematurely liquidated assets may trade at dislocated—or fire-sale—prices since investors have incentives to sell quickly, while potential buyers are unable to absorb the supply (Shleifer and Vishny, 1992; Mayer, 1995). The factors causing fire sales have been documented extensively.[1] Nonetheless, little is known about whether, and how, investors internalize fire-sale risk in their ex-ante portfolio decisions. Such rational internalization could in principle mitigate ex-post fire sales, reducing financial market runs (Bernardo and Welch, 2004). These are important questions since fire sales can result in large costs for individual investors, but also for society as they exacerbate economy-wide credit constraints and may result in feedback loops (Lorenzoni, 2008; Jeanne and Korinek, 2010).

This paper uses the U.S. residential mortgage market as a laboratory to study the ex-ante consequences of fire-sale discounts. Examining this market has the advantage that it consists of a large number of local liquidation markets (i.e., neighborhoods), each with relatively homogeneous assets (i.e., residential dwellings). Houses are collateral assets that lenders, under a foreclosure process, can repossess and auction to third parties, typically at a price well below market value (Anenberg and Kung, 2014; Chinloy et al., 2017; Ramcharan, 2020). Moreover, local house price discounts widen and are more persistent in the aggregate incidence of foreclosures (Campbell et al., 2011). Using comprehensive micro-level data, our paper shows that mortgage credit is reduced in markets where anticipated losses from future disorderly foreclosures are high. This suggests that the individual actions of lenders, by allocating credit away from high-risk areas, lower the economy-wide incidence of fire sales.

We hypothesize two channels through which fire-sale risk affects ex-ante credit. First, fire-sale losses are expected to be milder in markets with higher lender concentration. Lenders with a large share of local debt are more likely to internalize negative price spillovers when deciding to foreclose a mortgage as they hold more mortgages that are affected by this price spillover(Favara and Giannetti, 2017, derive this mechanism theoretically and provide

[1]For a comprehensive overview on fire sales in finance and economics, see Shleifer and Vishny (2011).

empirical evidence for it). This means that ex-post liquidation decisions are more efficient in the presence of high market share lenders, leading to lower fire-sale costs. By contrast, fire sales are expected to be more severe in dispersed markets as small lenders generate price spillovers that mainly manifest themselves as externalities to other lenders. Moreover, small lenders may want to "rush to the exit" (Oehmke, 2014), creating strategic complementarities in liquidation decisions. We thus expect a higher inclination to originate credit in markets that are more concentrated, both in terms of a lender's own market share, but also in terms of the dispersion of the residual market shares (i.e., the market share dispersion of all other lenders). Second, fire sales are more likely, and expected to be more severe, when locally active lenders are expected to get into financial distress at the same time. The risk of the latter is higher when these lenders hold overlapping portfolios as they are then exposed to the same shocks (e.g., Greenwood et al., 2015). A rational lender should therefore prefer originating credit in a market with more dissimilar lenders (Wagner, 2011). We hypothesize both channels to be weaker when foreclosure frictions (e.g., caused by bureaucracy) are high, as higher barriers to foreclose simply make fire sales less relevant.

Our empirical strategy involves regressing mortgage acceptance decisions on a lenders' own local market share, residual market concentration (excluding the lender herself), and portfolio dissimilarity with other local lenders. Yet, these variables may affect credit supply also through other channels. Therefore, we obtain identification from interactions with state-level legal foreclosure frictions. In the United States, legal fees (e.g., attorney, notary, court, trustee, etc.) a lender must pay for each foreclosure service substantially differ across states. There is evidence that states with expensive and long legal foreclosure processes more than halve lenders' propensity to foreclose on a delinquent borrower (Mian et al., 2015). Importantly, the literature shows that foreclosure laws do not correlate with any state-level economic conditions (Ghent and Kudlyak, 2011; Mian et al., 2015), establishing an exogenous treatment that is useful for empirical identification. See figure 2 for the cross-section of state legal costs.

To minimize the scope for unobserved heterogeneity, we saturate our models with fixed effects and base our analysis on granular application-level data, which allows us to disentangle credit supply from demand. We mainly focus on the period of the Global Financial Crisis for our baseline analysis. During this period foreclosures are salient and the markets for private securitizations are largely closed, providing for a cleaner setting for identification.

Our results show that a lender's propensity to approve mortgage applications decreases when her local market share is low, when the ownership of surrounding local mortgages is dispersed, and when other local lenders are similar to her. The estimated magnitudes are economically significant: a one-standard deviation increase in any of the three fire-sale risk proxies lowers the acceptance rate by an average of 1 percentage point. Importantly, all three channels significantly weaken, both in statistical and economic terms, in states with higher foreclosure frictions. Whereas our main analysis is based on individual mortgages, we also examine aggregate credit allocation across markets. We find that credit supply in neighborhoods with high fire-sale risk contracts relative to neighborhoods with low fire-sale risk, with economically large magnitudes. As we demonstrate, this suggests that (expected) nationwide fire-sale costs, measured per unit of credit, are reduced going forward.

To further mitigate the risk of endogeneity driving our results (e.g., a high market share may indicate operational synergies), we conduct an instrumental variable estimation. Following prior literature (Garmaise and Moskowitz, 2006; Favara and Giannetti, 2017), we exploit merger deals among large banks as a source of plausibly exogenous variation in a lender's market share. The analysis based on the instrumental variable method confirms, and even strengthens, the baseline estimates.

There are other non-exclusive channels through which fire sales and mortgage origination could be related. In particular, Giannetti and Saidi (2018) and Gupta (2019) propose that high-market-share banks have incentives to provide liquidity when collateral prices *are already* depressed, as this can prop up industry-wide collateral prices and benefit their existing portfolio borrowers (*propping-up* hypothesis henceforth). By contrast, our channels are based on lenders anticipating the risk of future fire sales. We disentangle these two mechanisms in two ways. First, we analyze loans extended for home construction. Such loans increase local housing supply, and should depress local collateral prices, rather than increasing them. Under the propping hypothesis lenders should hence avoid financing new houses, whereas fire-sale risk stems from both financing of new and existing houses. Consistent with the latter we do not find our proxies for fire sales to affect lending decisions in areas with high construction intensity in a statistically different way. Secondly, we exploit variation in borrower default risk for the loans to be approved. Borrower repayment ability is a key driver of fire-sale risk, but should not matter if the main purpose is to prop-up prices of existing collateral. Consistent again with the fire-sale risk interpretation of our results, we find stronger results for mortgage applications filed by riskier borrowers.

We conduct several additional tests to further the understanding of our results. First, we focus on loan applications in recourse states, where "underwater" – mortgage balance exceeding the value of the property – borrowers are less likely to strategically default, as a means to isolate exogenous default risk (Demiroglu et al., 2014). We find the results to be equivalent to our baseline analysis. Second, we find that fire-sale risk affects origination decisions of lenders with weak balance sheets more strongly. This is consistent with shorter and more uncertain horizons creating higher reliance on revenues from collateral sales (Morris and Shin, 2004; Cella et al., 2013; Ramcharan, 2020; Demirci et al., 2020). Third, we show that mortgage rates are lower when fire-sale risk is low. Hence, approval and pricing decisions are in line with each other. Fourth, we investigate actual credit origination and find the results to be similar to the ones obtained from mortgage approvals.[2] Finally, we find our results to be weaker outside the Global Financial crisis, consistent with fire-sale risk being less salient there.

Our study contributes to the literature linking credit supply to collateral fire sales. Several

[2] For a mortgage approval to translate into actual credit, borrowers should not reject the terms offered by the bank.

theoretical studies show that, in the presence of transaction costs and contractual incompleteness, the value of the option to liquidate collateral should affect the creditor's willingness to extend financing in the first place (Williamson, 1988; Shleifer and Vishny, 1992; Hart and Moore, 1994; Bolton and Scharfstein, 1996). Empirical studies on expected liquidation payoffs primarily analyze forces coming from potential buyers, such as their financial conditions or collateral redeployability (i.e., value in other uses). For example, several papers (Benmelech et al., 2005; Benmelech and Bergman, 2009; Ortiz-Molina and Phillips, 2014; Demirci et al., 2020) show that asset collateral redeployability positively affects loan size and maturity, and negatively affects interest rates and the number of creditors. By contrast, our paper is the first one, to the best of our knowledge, to examine variation in fire-sale costs arising from the supply side of the liquidation market, namely from differences in sellers' propensity to liquidate. For identification, we draw on a relatively recent literature that shows that stronger borrower protection laws negatively affect recovery values and lenders' propensity to foreclose ex-post (Mian et al., 2015). Consequently banks originate fewer and smaller loans ex-ante in states where the foreclosure process is more expensive (Pence, 2006; Dagher and Sun, 2016; Milonas, 2017; Degryse et al., 2020). The saturation of the model with tight geographical fixed effects allows us to look *within* narrow local markets, where the direct effect of legal costs on credit supply is constant.

We also contribute to the vast literature on market concentration in banking. A more concentrated banking sector may be prone to excessive risk-taking due to being too-big-to-fail (Stern and Feldman, 2004), it may impede the transmission of monetary policy (Scharfstein and Sunderam, 2016), or stifle innovation (Aladwani, 2001). By contrast, our results suggest that banking concentration can alleviate credit constraints by reducing the negative effects of fire sales. This effect is distinct from other beneficial channels of banking concentration, such as greater scope for relationship lending (Petersen and Rajan, 1995), or the mitigation of industry-wide shocks and credit booms (Giannetti and Saidi, 2018; Giannetti and Jang, 2021).

Finally, we contribute to the literature on bank similarity. Several studies have analyzed perverse incentives for and consequences of banks becoming more similar to one another, for example due to being too many to fail or being exposed to the same regulator (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012). Our study, however, provides evidence consistent with incentives for banks to become less similar, since this reduces their exposure to fire-sale losses going forward. In that vein, fire sales have a beneficial disciplining effect.[3] This echoes findings stressing that regulatory interventions ex-post (such as those that reduce the cost of fire sales to lenders) have potentially undesirable ex-ante implications (e.g., Perotti and Suarez, 2002; Acharya et al., 2011).

2 Empirical predictions

In this section, we derive testable predictions that link credit supply to drivers of fire-sale risk. We use these predictions as a basis for our empirical tests in Section 4.

The *liquidation value* of a collateralized loan corresponds to the recovery amount that, conditional on borrower's default, a lender can recoup after seizing the underlying asset and selling it to a third party. The price at which a collateral can be sold is often depressed due to asymmetric information, the need for immediacy, the absence of buyers that are efficient users for the collateral, and an excess of supply facing a shortage of demand for the collateral. The latter effect may even give rise to a disorderly rush to sell troubled loans, in order to avoid selling behind the rest of the market at even lower values (Morris and Shin, 2004; Bernardo and Welch, 2004). To protect themselves from fire-sale costs, rational lenders may target loans with lower anticipated liquidation losses.

From an empirical perspective, measuring ex-ante fire-sale risk is challenging. To understand their vulnerability to joint collateral liquidations, we assume that lenders form beliefs on the likelihood of future foreclosures by themselves, and others, given the most recent

[3] It is important to note that such discipline will always be insufficient to offset welfare losses due to fire sales (see, for example, Lorenzoni, 2008; Jeanne and Korinek, 2010).

state of a market they are operating in. This is a plausible assumption in the context of the US mortgage market, because financial institutions are required to publicly disclose their mortgage-portfolio allocations. As a result, financial institutions can be expected to have fairly common knowledge regarding lending portfolios.

2.1 Fire-sale risk channels

In this subsection, we draw on the existing literature on endogenous liquidation decisions by lenders to identify channels that relate credit supply to fire-sale risk, and construct associated empirical predictions.

When a lender forecloses defaulted mortgages, she increases the supply in the market for collateral assets, leading to lower prices for other properties that will be possibly foreclosed later on (Campbell et al., 2011). Hence, mortgage foreclosures impose a negative externality on other loans that are scheduled for foreclosure. The literature has shown that the extent to which this negative externality materializes ex-post depends on market structure. Consider a lender who is active in a given local market. The degree to which she will suffer from fire-sale externalities will, first, depend on her own market share. Lenders with a large share of local debt outstanding are more likely to internalize the negative externalities from foreclosures on their own portfolio of borrowers and, thus, avoid foreclosing all but the most troubled loans (for which foreclosure is the only option). Favara and Giannetti (2017) provide empirical evidence for this channel, showing that large lenders with substantial "skin-in-the-game" are more likely to renegotiate defaulted mortgages ex-post, resulting in lower fire sale discount per loan. Second, the externality will depend on dispersion in the *rest of the market*. Given her own market share, a lender will expect lower fire-sale losses when the other lenders in the market are more concentrated, as these other lenders will be less inclined to foreclose ex-post.[4]

Summing up, lenders are less exposed to fire sales when their local market share is large,

[4] Favara and Giannetti (2017) empirically show that on aggregate fewer foreclosures arise in concentrated markets than in dispersed ones.

and when the rest of the market is more concentrated.[5] Hence, we derive the following two predictions regarding loan originations:

Prediction 1 *A lender's incentive to originate a mortgage increases in her local market share.*

Prediction 2 *A lender's incentive to originate a mortgage increases if the residual local market (excluding her own share) is more concentrated.*

Prediction 1 and 2 are also consistent with risks arising from *disorderly* fire sales. Akin to bank runs, there are incentives to "run to the exit" in order to avoid liquidations at later stages of the fire-sale process, when prices are very depressed (Bernardo and Welch, 2004). Again, the incentives for such strategic behavior will be larger in fragmented markets: Oehmke (2014) provides a model showing that disordely liquidations are more likely in markets with higher dispersion because lenders then do not internalize price effects of their liquidation decisions.

The discussion so far has focused on fire-sale risk arising from coordination failures in foreclosure decisions. Keeping everything else constant, lenders can expect low collateral foreclosure prices in local markets with high dispersion. A second reason for why foreclosure prices are low arises when lenders are forced to collectively liquidate because of joint liquidity or capital needs (that is, when liquidations are driven by lenders' financial positions, not only borrower default). Ramcharan (2020) shows that declines in bank capital or liquidity lead to an increase in sales of bank-owned real estate at progressively worse prices.[6] This risk of joint liquidation is elevated when lenders have common asset exposures. Greenwood et al. (2015), in particular, show that banks suffer ex-post large fire-sale costs when they hold more

[5] In our empirical implementation we will identify both effects using variation across lenders within a given local market. This raises the issue of whether both effects can be independently identified. In Appendix A we develop a model of liquidation decisions and loan origination incentives and show that the two effects are driven by different parameters, thus allowing for identification.

[6] Since mortgages are some of the key assets on lenders' balance sheets and since mortgage default rates and bank profits tend to fluctuate with the business cycle, one would expect borrower and lender financial health to be correlated.

overlapping portfolios. Wagner (2011) shows theoretically that the gains from investing ex-ante in an asset declines if there is larger commonality with other investors in the same asset, due to higher fire-sale risk.[7] Notably, this joint-liquidation risk is driven by commonality in the entire asset portfolios of lenders, not just their portfolio in the local market. This mechanism leads to the following testable prediction:

Prediction 3 *A lender's incentive to originate a mortgage increases if her portfolio is dissimilar to the portfolios of the other lenders in the local market.*

Obviously, there are other channels that link market structure and portfolio overlap to origination incentives, irrespective of fire-sale risks. To isolate the latter, we exploit frictions in the mortgage foreclosure process. In particular, we focus on examining how the sensitivity and magnitude of the channels underlying predictions 1 to 3 vary when there is exogenous variation in the feasibility of collateral liquidations. Intuitively, one such source of variation corresponds to state judicial barriers associated with the foreclosure process. In the U.S., these legal costs (which are borne by lenders at various stages of the foreclosure process) differ widely across states and, importantly, are unrelated to economic conditions (Ghent and Kudlyak, 2011). As shown in Mian et al. (2015), when legal costs to foreclose are high, foreclosure is simply not an attractive option for any lender. Consequently, we argue that fire-sale-induced collateral prices should become much less relevant for private lending decisions. This leads to the following empirical implication:[8]

Prediction 4 *Foreclosure costs mitigate the impact of fire-sale risk on mortgage origination.*

[7]Georg et al. (2019) provide evidence from US Money Market Mutual Funds (MMFs) consistent with this. They find that MMFs are less likely to invest in assets if they have portfolios similar to other investors in these assets.

[8]Of course, one would expect acceptance rates to decline in state level foreclosure costs for all mortgage applications (the average of which would empirically be picked up by neighborhood fixed effects). Yet, this is effect is expected to be stronger for applications that would have low fire-sale risk in the absence of such costs.

3 Data

The empirical investigation of ex-ante effects of fire-sale risk requires data on lenders' mortgage allocations. This allows to characterize a lender fire-sale expectations in each neighborhood. Therefore, our empirical tests rely on the comprehensive dataset made available under the Home Mortgage Disclosure Act (HMDA). It contains detailed information on nearly the full universe of mortgage applications in the United States. Most importantly for our analysis, individual application records include the lender's decisions (whether to originate, and possibly whether to securitize within the same calendar year) as well as the location of the property up to the census tract.[9] In addition, the dataset contains information on the loan itself (such as loan purpose, amount and price), the applicant, and the type of underlying property securing the mortgage application. Following prior literature, we exclusively focus on mortgage applications for purchasing 1-4 family dwellings, since foreclosure laws may differ for other housing types and since government bailout programs may influence credit supply for other types of applications (e.g., mortgage refinancing). To minimize the potential impact of manual entry outliers, we truncate the final application dataset on the loan amount at 5% (on both sides of the distribution).

We source pre-crisis annual accounting data from Call reports and Thrift Financial Reports to measure financial distress of lending institutions. Furthermore, we use the annual information on locations and deposit amounts of all bank branches in the US from the Summary of Deposits database, available at the Federal Deposit Insurance Corporation (FDIC), to calculate instrumental variables for our analysis in Section 4.2.

Private securitization is common in the U.S. mortgage market (using structured products, and conduits), which potentially complicates any empirical analysis on mortgage credit supply. For example, the prospect of securitization may contaminate credit origination decisions (e.g., see Berndt and Gupta (2009) for the syndicated corporate loans, and Keys et al. (2010);

[9] A census tract ("neighborhood" in the empirical analysis) is a small area within a county and generally contains between 2,000 and 4,000 inhabitants.

Dell'Ariccia et al. (2012); Rajan et al. (2015) for the mortgage market). To minimize such issues, we focus our main analysis on mortgage applications made over the Global Financial Crisis (2007 to 2010).[10] During this period the private securitization market was mostly frozen. We construct fire-sale risk proxies using only pre-crisis information, specifically from 2004 to 2006, to mitigate any reverse causality concerns.

Since foreclosure spillovers arise within a small geographical radius (Campbell et al., 2011; Anenberg and Kung, 2014; Mian et al., 2015), we define a local market at the neighborhood level using the census tract structure. For some of our analyses, we use data that are only available at the ZIP-code level. Therefore, we match neighborhoods to ZIP codes using data from the Missouri Census Data Center.[11] We assign each mortgage application received by an affiliate or subsidiary lender to her respective parent company using information from the Federal Reserve's National Information Center (NIC), when this information is unavailable in HMDA.[12] To be able to construct pairwise portfolio overlaps, we only consider lenders that originate mortgages in at least two neighborhoods. After applying these standard filters, our main application-level dataset contains nearly 4 million mortgage applications, made to about 5,000 lenders for properties in 50,000 neighborhoods in the period from 2007 to 2010.

3.1 Variables construction

Our primary analysis examines how lender i's decision to finance mortgage applications for properties in neighborhood n is affected by her own local market share, the concentration of market shares of the other lenders in the same neighborhood as well as her portfolio overlap with local potential sellers. We follow Favara and Giannetti (2017) and measure a lender's own local market share by her retention share in the neighborhood over the 2004-2006 period:

[10] Mortgage Credit Default Swap (ABX) indices indicate that turmoil in subprimce markets began in February 2007 (Brunnermeier, 2009).

[11] Because a few census tracts cross two (or more) ZIP codes, we assign these neighborhoods to the overlapping ZIP code with the largest portion of housing stock therein. See more at `https://mcdc.missouri.edu/help/data-allocation/`.

[12] The types of lenders that need to report under HMDA the applications they receive consist of commercial banks, thrifts, and mortgage companies. See Table 8 in the Appendix for a breakdown of the coverage by lender type and year.

$$RetShare_{i,n,0406} = \frac{RetLoans_{i,n,0406}}{TotalLoans_{n,0406}}$$

where $RetLoans_{i,n,0406}$ is the number of mortgages that lender i has retained on her balance sheet in neighborhood n while $TotalLoans_{n,0406}$ is the total number of mortgages originated - both retained *and* securitized - by all lenders in the same neighborhood over the same period. This variable will be used to test Prediction 1.

We measure the concentration of competitor market shares by constructing residual concentration measure of outstanding mortgages $HHI_{(i),n,0406}$. For each lender i we exclude her own retained loans, and define $HHI_{(i),n,0406}$ as follows:

$$HHI_{(i),n,0406} = (HHI_{n,0406} - RetShare^2_{i,n,0406})\Big(\frac{TotalLoans_{n,0406}}{TotalLoans_{n,0406} - L_{i,n,0406}}\Big)^2$$

where $HHI_{n,0406}$ is the Herfindahl-Hirschman Index (HHI) in neighborhood n defined as $\sum_j (RetShare_{j,n,0406})^2$; $TotalLoans_{n,0406}$ is the total number of loans originated by all lenders in that neighborhood and $L_{i,n,0406}$ is the number of loans that lender i has retained *and* securitized in the neighborhood n. A lender-specific vector $HHI_{(i),n,0406}$ lies within 0 and 1, with larger values reflecting more concentrated creditor structure and thus lower fire-sale risk, holding everything else constant (Favara and Giannetti, 2017; Oehmke, 2014). This variable will be used to test Prediction 2. Note that $HHI_{(i),n,0406}$ varies within neighborhood across lenders and does not mechanically correlate with $RetShare_{i,n,0406}$.[13] This allows for identification using both lender and neighborhood fixed effects.

To test Prediction 3, we construct a portfolio dissimilarity measure following the two-step approach of Georg et al. (2019). First, we calculate the pairwise "Euclidean distance" in *nationwide* retained-mortgages portfolios between lender i and lender j

[13]For example, when a bank has a high own market share, residual market concentration may be either small or large. This is consistent with the within-neighborhood correlation between $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ in our sample being 0.37, and thus having the opposite sign that would arise under a mechanical correlation. In fact, the positive correlation is consistent with local markets consisting of a small number of large banks and a larger number of small banks.

$$EuclDist_{i,j,0406} = \sqrt{\sum_{n=1}^{N} \Big(\frac{RetLoans_{i,n,0406}}{TotRet_{i,0406}} - \frac{RetLoans_{j,n,0406}}{TotRet_{j,0406}}\Big)^2}$$

where $TotRet_{i,0406} = \sum_n RetLoans_{i,n,0406}$ is lender i total number of retained mortgages across all neighborhood in all states and the ratio $\frac{RetLoans_{i,n,0406}}{TotRet_{i,0406}}$ measures the relative portfolio weight - in terms of retained mortgages - allocated by lender i to neighborhood n. By construction, each lender i's portfolio weights add up to one, that is $\Sigma_{n=1}^{N} \frac{RetLoans_{i,n,0406}}{TotRet_{i,0406}} = 1$. In our data, an average lender has retained mortgages in 514 neighborhoods.

$EuclDist_{i,j,0406}$ measures portfolio dissimilarity between lender i and another lender j. In a second step, we calculate a measure of average dissimilarity of lender i with all other lenders in a neighborhood, $wDissimilarity_{i,n,0406}$. We do this by aggregating the pairwise distances $EuclDist_{i,j}$, weighted by the importance of neighborhood n in lender j's portfolio:[14]

$$wDissimilarity_{i,n,0406} = \sum_{j \neq i} \frac{RetLoans_{j,n,0406}}{TotRetLoans_{j,0406}} \times EuclDist_{i,j,0406}$$

Intuitively, larger values of $wDissimilarity_{i,n,0406}$ imply that in neighborhood n, lender i competes with other lenders that have less similar portfolios to her, decreasing joint liquidation risk for lender i (Prediction 3). This and other variables are defined in table 1.

[Table 1 here]

To examine whether fire-sale risk is attenuated by exogenous liquidation costs (Prediction 4), we complement our application-level dataset with information on foreclosure laws at state-level. We use the most granular and comprehensive definition of foreclosure legal costs, that is, the Fannie Mae Foreclosure Timeline index. Fannie Mae publicly outlines

[14]In line with the spirit of most theoretical models on fire sales, the linear price impact of a fire sales is proportional to the total (dollar) size of the assets financial institutions liquidate in a market (Shleifer and Vishny, 2011). Therefore, in equilibrium, a lender can expect higher fire-sale discount the larger the amounts of liquidations.

in their Servicing Guide the main Attorney's and Trustee's fees governing each state (in U.S. dollars). As in Dagher and Sun (2016), we standardize the index by the cost level of the most expensive state (i.e., NY) to construct an index $LegalCost_s$ bounded between 0 and 1.[15] To examine Prediction 4, we interact retention shares, residual concentration and portfolio dissimilarity measures with $LegalCost_s$. We focus our empirical analysis on these interactions, for reasons of identification.

Lastly, while our analyses primarily focus on approval decisions, we also use information on mortgage interest rates for some of our additional analyses. HMDA requires lenders to report the mortgage interest rate whenever it is higher than the rate on Treasury securities of comparable maturity. We create a dummy variable for each origination, $HighCost_{i,n,0710}$, that takes the value of one for any positive HMDA rate spread, and zero if no rate is reported.

[Table 2 here]

Table 2 describes the summary statistics of the variables used throughout the empirical analysis. Panel A contains the variables used in the baseline analysis and shows that lenders reject roughly one in seven (13.82% of) mortgage applications. The origination rate is very similar to the approval rate, which suggests that very few borrowers decline the lender's offer ex-post. Conditional on acceptance, the probability for a mortgage to come with a high interest rate is 7%. On average, a lender's local retention share equals 2.5%. The average concentration of competitor market shares $HHI_{(i),n,0406}$ equals 0.013. Notably, both $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ averages are small over the full sample by construction, since we scaled retained market shares by all - sum of retained *and* securitized - local mortgages (as in Favara and Giannetti, 2017). The dissimilarity index vis-a-vis other local lenders is low on average (.045), reflecting that there is a high degree of portfolio overlap.

[15]Figure 2 in the Appendix plots the state-level costs. For more details on the measurement of foreclosure costs, see `https://singlefamily.fanniemae.com/media/18696/display`;

4 Empirical strategy and results

We employ a linear probability model (LPM) at the mortgage application-level to study the extent to which lender i's decision to grant a mortgage depends on the associated fire-sale risk.[16] The baseline model takes the form:

$$Appr_{i,n,m,0710} = \beta_1 FSR_{i,n,0406} + \beta_2 FSR_{i,n,0406} \times LC_s + \gamma' X_{m,0710} + \eta'_{i,n,t} + \varepsilon_{i,n,m,t} \qquad (1)$$

where the dependent variable $Appr_{i,n,m,0710}$ equals one if lender i approves a borrower m application for a house in neighborhood n, in year $t \in [2007; 2010]$. The vector $FSR_{i,n,0406}$ is one of the (inverse) fire-sale risk proxies (i.e., $RetShare_{i,n,0406}$, $HHI_{(i),n,0406}$, or $wDissimilarity_{i,n,0406}$); LC_s is the (time-invariant) regulatory foreclosure cost of the state s that contains neighborhood n; $X_{m,0710}$ is a vector of borrower or application controls, such as gender, ethnicity, loan amount, debt-to-income ratio, and a $jumbo$ dummy,[17]; finally, $\eta_{i,n,t}$ is a vector of lender, neighborhood, and year fixed effects, which absorb any time-invariant effects such as foreclosure or mortgage demand, as well as any common trends over time (Petersen and Rajan, 2002; Benmelech et al., 2005). Following Predictions 1-3 we expect $\beta_1 > 0$ as lower fire-sale risk (that is, larger values for $FSR_{i,n,0406}$) should increase lending. The interaction term is expected to be negative ($\beta_2 < 0$) as barriers to foreclosures mitigate the relevance of potential fire sales (Prediction 4). Standard errors are clustered at ZIP code-level to account for residual correlation at the regional level. Table 3 shows the coefficient estimates of the baseline model of Equation (1).

[Table 3 here]

[16] With $N \to \infty$ and T fixed, probit or logit models produce inconsistent estimates and have problems converging, while a linear probability model delivers $\sqrt{N}$ consistent ones (Wooldridge, 2002). Moreover, given the high-dimensional fixed effects in our loan application level specification, a LPM is computationally more efficient (Dell'Ariccia et al., 2012; Dagher and Sun, 2016).

[17] Mortgages with a balance exceeding the securitization threshold for Government-Sponsored Enterprises (GSEs) of $416k and with an Debt-to-Income ratio exceeding 80% are commonly called "jumbo" mortgages. Including this dummy in our model controls for loan-specific liquidity (Loutskina and Strahan, 2009), and it is still needed in models covering in-crisis sample periods (Dagher and Kazimov, 2015).

The first column shows that the probability of a lender approving an application increases in her (prior) retention share in the neighborhood (positive and significant coefficient on $RetShare_{i,n,0406}$). Column 2 adds the interaction term with LC_s. The negative and statistically significant coefficient is consistent with legal foreclosure frictions mitigating the relevance of disorderly liquidation risk for origination decisions. The third and fourth columns append the residual concentration to the model. Column 4 shows, first, that credit supply (approval rate) increases in the concentration of mortgages retained by other lenders (larger values of $HHI_{(i),n,0406}$).[18] It is worth to note that the inclusion of residual market concentration barely alters the coefficient on the retention share, indicating that the channels operating through own market share (Prediction 1) and residual market share (Prediction 2) are distinct. Column 4 shows that the effect of residual market concentration is weakened in states with large foreclosure costs (negative and significant coefficient on $HHI_{(i),n,0406} \times LC_s$).

Finally, the last two columns add the portfolio overlap channel to the specification. In column 5 we can see that the coefficient on $wDissimilarity_{i,n,0406}$ - as well as those on the previous channels - is positive and statistically significant, suggesting that the more dissimilar lender i's portfolio is to its competitors in neighborhood n, the higher the probability for lender i to accept a mortgage application. Column 6 shows that the effect of portfolio dissimilarity is weakened when foreclosure costs are higher.

The empirical results in Table 3 thus confirm the predictions derived in Section 2.1. Whereas the direct links between the various proxies of fire-sale risk and loan origination could also be driven by other channels (e.g., retention share may proxy for economies of scale which in turn affects incentives to originate), such channels would typically not predict dependence on foreclosure costs (that is, the interaction terms).[19]

Since standard errors may be compressed due to the large sample size, it is important to

[18]Our model of market shares and origination incentives (Appendix A) predicts that the effect of residual market concentration is weaker (less positive) when the overall market is concentrated. Consistent with this, we also examined how the coefficient of $HHI_{(i),n,0406}$ to vary across markets in terms of overall concentration ($HHI_{n,0406}$). An interaction term between $HHI_{(i),n,0406}$ and $HHI_{n,0406}$ added to the specification under column 3 obtains a negative coefficient.

[19]In the robustness tests (Section 4.3), we further examine alternative explanations.

also assess economic significance. In column 3, one-standard deviation increases in retention share, residual creditor concentration, and portfolio dissimilarity are associated with an average acceptance rate increase of 1.3%, 1.3%, and 0.85%, respectively. Given the sample size of 3.8 millions applications, each of these hypothetical shocks translate into 27,740 to 41,800 additional originations during our sample period. The impact of legal foreclosure costs on these effects is also meaningful: the same three shocks respectively lead to a 1.8%, 2.4%, and 1.3% higher approval probability in California (where the liquidation costs index LC_s is 0.46) while equivalent shocks would increase approval rates by only 1.27%, 1.34%, and 0.68% in a state with high foreclosure frictions such as South Carolina (where LC_s is at 0.75).

4.1 Credit reallocation

Figure 1 presents an alternative exercise, to assess the *aggregate* implications of fire-sale risk. The figure plots changes in credit supply at the neighborhood level against (pre-crisis) average local market concentration (Panel (a)) and portfolio dissimilarity (Panel (b)), weighted by lenders' retention shares. Change in credit supply is measured by the change in total mortgages originated during 2007-2010 relative to the period 2004-2006 (following the approach of Dagher and Kazimov, 2015). Consistent with the micro-evidence reported in the baseline analysis, we see that lending declines less in concentrated neighborhoods, and in those where lenders have dissimilar portfolios (because the slopes of the regression lines are positive). Importantly, the slope of the regression line for neighborhoods with high foreclosure costs (orange line) is flatter than the corresponding line for low foreclosure costs (red line), consistent with Prediction 4.[20]

The analysis thus suggests that credit is allocated from areas with high fire-sale risk to

[20]The slope estimates in Figure 1 still suggest economically large effects of fire-sale risk, even larger than the one obtained from the mortgage-level regressions. In particular, a one-standard deviation increase in the local market concentration increases mortgage lending by around 2.6 (2.8) percentage points in areas with high (low) foreclosure costs, whereas the corresponding figures for an increase in the dissimilarity index are 2.3 (2.5) percentage points.

areas with low fire-sale risk. This reallocation is expected to reduce overall fire-sale costs in the economy. Specifically, in Appendix A.3 we examine the effect of credit reallocation from a neighborhood with low concentration to one with high concentration. Under the assumption that this credit reallocation does not affect market structures, we show that such reallocation lowers total costs from mortgage delinquencies in the economy.[21]

4.2 M&A exogenous shocks

Our identification strategy based on exogenous variation in legal foreclosure costs goes a long way in ruling out alternative channels, in particular arising with respect to a possible endogeneity of market structure. Nonetheless, in this section we conduct an Instrumental Variable (IV) analysis. Following Favara and Giannetti (2017), we use large ($\geq$ \$1 billion in assets) M&As in the banking sector as events that affect market conditions (and hence fire-sale risk proxies) for exogenous reasons. These deals are typically taken at the top-management level, rather than based on fire-sale synergies of individual neighborhoods, making the exclusion restriction likely to hold. We identify 253 surviving banks involved in a M&A at some point between 2004 and 2006 through the list of deals of the Federal Reserve Bank (FRB) of Chicago. Using this information and following Favara and Giannetti (2017) methodology, we construct a measure of local M&A intensity using bank branch data from the Summary of Deposits:

$$Mergers_{i,z,0406} = \frac{\sum SurvivorBranches_{i,z}Deposits}{\sum TotalBranches_{z}Deposits},$$

where $\sum SurvivorBranches_{i,z}Deposits$ is the sum of deposits survivor banks have in their branches in a ZIP code z, and $\sum TotalBranches_{z}Deposits$ is the sum of all banks deposits in the same area. The ratio $Mergers_{i,z,0406}$ denotes the merger intensity (and deposit inflows)

[21] To the extent that fire sales are zero-sum (benefitting buyers at the expense of sellers) such costs should not be equated to welfare losses. However, fire sales usually cause aggregate inefficiencies as the cause feedback loops and/or can cause costly bankruptcies of financial institutions (see for example Lorenzoni (2008); Jeanne and Korinek (2010)).

of the survivor bank i within a ZIP code z. Because of positive exogenous shocks, banks can retain more mortgages, and $RetShare_{i,n,0406}$ is expected to increase with merger intensity. The results of the IV estimation are presented in Table 4.

[Table 4 here]

The first two columns of Table 4 show the results of the first stage estimation. As before, we include borrowers' controls and lender, year and neighborhood fixed effects. Higher merger intensity (higher values for $Mergers_{i,z,0406}$) expands the liability side of the balance sheet, which allows banks to retain more loans. The overall positive and statistically significant coefficients on the first stage variables ($Mergers_{i,z,0406}$ and $Mergers_{i,z,0406} \times LC_s$) are consistent with this prior. Most importantly, the second stage results (third and fourth columns) confirm our earlier results.

Notably, the economic magnitude of the IV analysis is larger than the one of the OLS (Table 3, column 6), consistent with Favara and Giannetti (2017). Focusing on the last column, the effects are now more than threefold relative to OLS: a one standard deviation shock in $RetShare_{i,n,0406}$, in $HHI_{(i),n,0406}$ and in $wDissimilarity_{i,n,0406}$, lead to respectively a 4.5%, 7.1%, and 3.3% higher approval probability in California (where LC_s is 0.46), while 0.46%, 1.5%, and 0.15% in South Carolina (where LC_s is at 0.75). An explanation for the higher effects is that instrumenting a local retention share with M&A shocks captures changes in merged banks only and leads to the largest changes in concentration. These institutions are likely the ones most efficient, on average. They should also be arguably the entities that use a centralized risk management system for their lending decisions and should be hence able to anticipate fire-sale risk more systematically.

4.3 The propping-up channel

There is an alternative channel through which high market shares could make loan origination more attractive (Prediction 1 and 2). Once a market is distressed, lenders with larger market shares may have incentives to "prop-up" local house prices by extending more mortgage credit. This mechanism benefits their existing lending portfolio, among others, by disincentivizing borrowers to strategically default (Giannetti and Saidi, 2018; Gupta, 2019; Elul et al., 2020).[22] In contrast, in our predictions lending decisions are driven by the fear of future fire-sale losses, not by the current fire sales themselves. Below, we conduct two additional tests to try and separate the *propping-up* hypothesis (an ex-post perspective) from anticipating fire-sale risks (which are ex-ante channels).

For our first test, we examine loans to finance new houses (construction loans). Such loans are undesirable under the *propping-up* channel, as they increase local housing supply and hence depress prices (rather than increasing them). By contrast, the fire-sale risk channels should not affect mortgage lending for existing and new housing in a statistically different way. Unfortunately, HMDA application data does not specify whether a borrower applies for a mortgage for a newly built property or an existing one. To overcome this limitation, we create a measure of home construction intensity at the neighborhood level to proxy for construction loans. We obtain Building Permit Survey (BPS) data from the U.S. Census Bureau, Manufacturing and Construction.[23] This dataset contains annual residential building permits released, at the census tract-level for all U.S. states. The variable $NewHous_{n,0710}$, with support on the unit interval, is defined as the number of permits for new houses in a

[22] Giannetti and Jang (2021) investigate a related point. The study syndicated lending in years immediately prior to a banking crisis, that is, when informed banks may anticipate declines in collateral values. They find that large local lenders extend less credit in such periods, but this behaviour is not present in credit booms that are not followed by crises.

[23] Note that the BPS dataset does not fully match with HMDA for three reasons: first, BPS does not include all neighborhoods; second, some neighborhoods with construction permits could even receive no HMDA applications in that year; lastly, matched neighborhoods could be the ones where banks received fewer applications. As a result, the number of observations drops to one fourth with respect to the baseline sample, that is, to 1 million mortgage applications coming from nearly 15 thousand distinct neighborhoods. For more information, see `https://www.census.gov/construction/bps/`.

census tract n in year t as a fraction of total housing stock in that census tract.

For our second test, we exploit heterogeneity in borrower default risk. Under the *propping-up* hypothesis, the default likelihood of the applicant does not play a specific role, as the ultimate purpose is to stimulate local house prices. Fire-sale risk, by contrast, closely depends on borrower default risk. We use the Loan-to-Income ratio (LTI), defined as the ratio between the loan amount requested and the annual income of the applicant and denoted by LTI_m, to proxy for borrower credit risk.

Table 5 contains the results of both tests. To avoid identification from triple interactions that are hard to interpret, we replace the interactions with foreclosure costs by interactions with home construction intensity and interactions with the loan-to-income ratio (compared to specification 6 in Table 3).

[Table 5 here]

Panel A contains the analysis using residential construction intensity. The first column of Table 5 shows coefficient estimates of the new specification, keeping the same controls and fixed effects as in the baseline (column 6 of Table 3). The first column shows that all coefficients are positive and statistically different from zero as before. In column 2 and 3, we include interactions with $NewHous_{n,0710}$, on all mortgage applications that BPS offers data for. Coefficients on $RetShare_{i,n,0406}$, $HHI_{(i),n,0406}$ and $wDissimilarity_{i,n,0406}$ are still positive and statistically significant. The interaction coefficients are not statistically significant, other than $HHI_{(i),n,0406} \times NewHous_{n,t}$, which takes the opposite sign as the one predicted by the *propping-up* hypothesis. [24] We obtain similar results if we change the definition of construction intensity in column 3, that is when $NewHous_{n,0710}$ equals one if the number of houses newly built in neighborhood n is higher than the county-average in a year, and zero

[24] The positive sign on this interaction might be explained by the fact that loans for new houses are riskier, and hence pose higher fire-sale risk.

otherwise. The coefficient estimates on the interaction terms are all statistically insignificant.[25] Thus, our analysis of mortgage acceptance across areas with differing construction activities fails to deliver any evidence consistent with the *propping-up* channel.

In panel B we examine how the effects differ across borrower default risk. Column 4 serves as benchmark. In column 5, we include interaction terms of the borrower default risk measure, LTI_m, with either fire-sale risk proxies. We find that only the interaction with $RetShare_{i,n,0406}$ is positive. However, this may be due to using an absolute measure of credit risk, when in fact credit standards differ substantially across local markets. Therefore, in column 6 we change the definition of variable LTI_m to a dummy taking value of one if the borrower LTI is higher than the annual county-average and zero otherwise (as $NewHous_{n,0710}$ dummy in column 3). In this case, all interaction coefficients are positive and statistically significant. This is consistent with higher fire-sale risk anticipation for riskier borrowers. By and large, although we cannot perfectly rule this alternative hypothesis (out of the scope of this paper), both exercises provide some evidence that is more in line with the fire-sale risk channel than with the *propping-up* hypothesis.

4.4 Further analyses

Negative home equity represents an important reason for households to strategically default (Guiso et al., 2013). In particular, almost 40% of defaulting households in the United States have a debt outstanding that is higher than the value of their house (Gerardi et al., 2017). Strategic defaults could add additional pressure on housing markets and lead to additional fire-sale losses (compared to the mechanisms described in Section 2.1). To abstract from strategic default risk affecting lending decisions, we repeat the analysis conducted in the baseline Equation (1) for a sub-sample of states with recourse laws only (41 out of 51 states,

[25] New residential buildings may prop up - instead of decrease - local prices, through an indirect amenity effect. Following the housing economics literature, we also focus on richest neighborhoods (those with household income above the MSA median), where existing houses at the margin do not benefit from new services (Simons et al., 1998; Ding et al., 2000), and still find insignificant coefficients on the fire-sale risk variables interacted with $NewHous_{n,t}$ (not shown for brevity).

see Figure 2 in the Appendix). In these states (orthogonal to judicial costs, see Ghent and Kudlyak, 2011) lenders are entitled to a deficiency judgement. Should the foreclosure payoff not be sufficient to cover losses, lenders can collect also other assets of the borrower. We present the results of this analysis in column 1 of Table 6, which confirm our earlier results (estimates are even slightly larger).

[Table 6 here]

Next, we investigate whether fire-sale risk considerations vary with the financial strength of the lender. The risk of joint liquidation arising from insufficient capital or liquidity (Prediction 3) is clearly higher for weaker financial institutions. Additionally, weak lenders have been shown to be forced to foreclose properties that they rather would not as a means of generating liquidity and shed risk (Ramcharan, 2020). Thus, fire sale risk arising from borrower default (Prediction 1 and 2) is also expected to be higher for weaker lenders. We follow Ramcharan (2020) and proxy lender financial health by (tier 1) capital divided by (risk-weighted) assets, taken as annual averages. Since lenders in our dataset are very diverse in liability structure (e.g., depository vs. non-depository institutions) and face different regulatory regimes, this measure is conditional on lender type. Specifically, we consider from each category (i.e., commercial bank, credit union, or thrift) only the weakest quartile according to our measure of financial health. Column 2 considers mortgage acceptances in this subsample. As predicted, all estimates are substantially larger in magnitude than in the baseline. Interestingly, the coefficient on $wDissimilarity_{i,n,0406}$ increases the most (in relative terms), consistent with the joint liquidation risk being directly driven by the financial health of the lender (Wagner, 2011).

In column 3, we do a sub-sample analysis on the riskiest borrowers. These are defined as the borrowers with an LTI higher than the county-year average (similarly to column 6 in Table 5). The coefficients increase in magnitude with respect to the baseline, suggesting that lenders rationally perceive higher fire-sale risk arising from lending to riskier borrowers.

Next, we run the same specification as in Equation (1) focusing on second-lien and unsecured mortgage applications in HMDA. For second-lien mortgages the decision to foreclose may not be with the originating lender (in particular if she is not also the first-lien lender), whereas collateral is irrelevant for unsecured lending. We would thus expect our fire-sale risk channels to be weaker for these types of applications. Column 4 shows that coefficients on fire-sale risk proxies for this sample are insignificant, except for $RetShare_{i,n,0406}$. A possible explanation for the significant coefficient on $RetShare_{i,n,0406}$ is that the originator of the second lien is more likely to also hold the first lien when $RetShare_{i,n,0406}$ is higher.

Column 5 enriches our baseline regression specification with lender size as a control. This is potentially important since large lenders may be better able to overcome foreclosure frictions. Since lender size (at the national level) and local market share may be correlated, this may potentially explain a significant interaction effect between market share and foreclosure costs. We measure lender size as average assets over the period 2004-2006. Column 5 shows that the results on the main coefficients remain in line with priors and statistically significant.

Our sample consists of loan applications made *during* the GFC, arguably when fire-sale risk was most salient for lenders. During that crisis, however, several government rescue packages, such as the Troubled Asset Relief Program (TARP), were implemented. This may possibly confound our analysis. We therefore conduct a robustness test where the sample consists of applications made during 2007 only. A second advantage of looking at that sample is that in 2007 there was no foreclosure crisis yet, thus fire-sale risk was salient but did materialize yet, allowing us to further separate future risks from any concurrent troubles. In column 1 of Table 7, we can see that the results are very similar to the baseline sample (column 6, Table 3).

[Table 7 here]

Next, we examine whether fire-sale risk also affects lending decisions after the crisis period. We would expect the results to weaken, for several reasons. First, loans extended outside the crisis are likely to be safer, hence less likely to be collectively foreclosed, resulting in fewer fire sales (e.g., Lorenzoni, 2008). Additionally, lenders are likely to be in better health, and hence joint liquidation risk is no longer elevated. Third, fire sales may simply be less salient for lenders, and hence affect lending decisions less (Gennaioli et al., 2012). Lastly, post crisis securitization markets were operative again, potentially permitting lenders to pass on mortgages with high fire-sale risk.

Column 2 in Table 7 reports regression results where the dependent variable is mortgage approval during 2011-2014. We still condition on fire-sale risk proxies from 2004 to 2006 as market conditions and lender portfolios during a crisis will be less informative about structural fire sale risk. We can see that market power and concentration (measured by $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ respectively) as well as their interaction with foreclosure costs are still significant with the expecting sign. However, the size of the effects is smaller than their equivalent in-crisis estimates, as expected. The coefficients on portfolio dissimilarity are now insignificant, possibly indicating that lenders were in much better health post-crisis, making simultaneous liquidations far less likely.

We next examine whether fire-sale risk also affects mortgage rates. Conditional on accepting a mortgage, a lender should require a higher compensation when fire-sale risk is high (as predicted by the model in Oehmke, 2014). In addition, lender decisions on interest rate and mortgage approval may, to a certain extent, be substitutes.[26] We re-estimate Equation (1), replacing the dependent variable with the high-cost dummy $HighCost_{i,n,0710}$, which equals one if the spread with a US treasury rate of similar maturity (as defined in HMDA) is strictly positive and zero otherwise. The coefficients on $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ in column 4 are negative and statistical significant, while interaction coefficients are positive and mostly statistically significant. The respective signs suggest that lenders require lower interest rates

[26]Note that this may lead to either under- or over-estimation of the fire-sale risk effect in the mortgage approval regressions.

when fire sales are less pronounced.

We also consider actual loan originations. A loan is only originated if subsequent to mortgage approval by the lender, the borrower also approves the loan and does not eventually withdraw her application. Mortgage approvals (by lenders) may not translate into new credit if borrowers reject offers due to unfavorable mortgage terms. We therefore replace $Approved_{i,n,0710}$ by $Orig_{i,n,0710}$ as the dependent variable, where $Orig_{i,n,0710}$ takes value of one if the mortgage is originated (accepted by both the lender *and* borrower) and zero otherwise. The results in column 5 are very similar to our baseline results in column 6 of Table 3.

Lastly, we also take into account the possibility of securitization. If a lender is planning to securitize a loan, fire-sale risk considerations are irrelevant to her. We thus disregard originated loans that were securitized later (either privately or through GSEs, essentially assuming perfect foresight with respect to the securitization decision). In the last column of Table 7, we replace our approval decision with $Retained_{i,n,0710}$, which takes value of one if the lender accepts and retain in her balance sheet a borrower application, and zero for either rejections or securitizations (either private and GSEs). As in the previous column, borrower withdrawals are excluded from the sample (approximately 7%). The results remain similar.

5 Conclusion

This paper examines lenders' incentives to internalize fire-sale risk into their mortgage lending decisions. We study mortgage applications in all U.S. states and build proxies of fire-sale risk using channels emphasized in prior literature. We find that foreclosure supply affects credit supply by lowering acceptance rates on mortgage applications. We also show that these effects decrease in states where legal foreclosure costs are higher, strengthening identification. An analysis of mortgage interest rate provides results consistent to the approval results: lenders charge higher rates when fire-sale risk is high, but this effect is mitigated in the presence of foreclosure frictions.

The internalization of fire-sale risk suggests that banks, by maximizing their private payoffs from lending, lower the incidence and severity of fire sales. Financial institutions rationally shift credit allocations from the areas with high fire-sale risk to areas with low fire-sale risk. These dynamics make local mortgage markets more concentrated and lenders more diverse, possibly reducing inefficient fire sales going forward, and improving financial stability.

Our analysis have noteworthy implications for policy. Our results suggest that the existence of fire sales has important disciplining effects for banks ex-ante. Policies that seek to lessen the costs of fire sales to banks ex-post (such as through regulatory forbearance) may hence have unintended consequences, by creating moral hazard ex-ante (due to higher risk-taking). If anything, our results suggests that regulatory efforts should focus on strengthening lenders' incentives to internalize inefficiencies fire-sale risk, rather than focusing solely on addressing ex-post inefficiencies from fire sales.

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Tables

Table 1: Variables Definition

Variable	Definition	Variable	Definition
$Approval_{i,n,0710}$	Dummy variable, taking a value of one if lender i approves a borrower's mortgage application for a house in census tract n, in a year over 2007-2010; zero if rejected;	$LoanToIncome$	Loan Amount requested as a fraction of the borrower's annual income;
$Origination_{i,n,0710}$	Dummy variable, taking a value of one if a mortgage application is originated, that is accepted by both lender i and the borrower; zero if the either party rejects it;	$Risky$	Dummy variable, taking a value of one if a borrower's LTI ratio is equal to or above the county's average LTI; zero otherwise;
$HighCost_{i,n,0710}$	Dummy variable, taking a value of one if the rate charged on mortgage originations is higher than the rate on a Treasury security of similar maturity; zero otherwise;	$NewHous_{n,0710}$	Annual number of home construction building permits as a fraction of the housing stock in a census tract n;
$RetentionShare_{i,n,0406}$	Number of mortgages that lender i originated and retained on the balance sheet as a fraction of total mortgages originated over 2004-2006 in census tract n;	$HighNewHous_{n,0710}$	Dummy variable, taking a value of one if $NewHous_{n,0710}$ is equal or larger than the county-year average; zero otherwise;
$wDissimilarity_{i,n,0406}$	Euclidean Distance between each pairwise lender's retained mortgage-portfolio, aggregated for each lender i by the retention share of all other lenders ($\neq i$) in census tract n;	$WeaknessQ_i$	Discrete variable that assigns a lender i to one of the weakness quartile-buckets based on its Tier 1 capital ratio, averaged over 2004-2006, by type (commercial banks, thrifts, credit unions);
$HHI_{(i),n,0406}$	Herfindahl–Hirschman Index, calculated as the sum of lenders' retention shares in a census tract n, excluding lender i;	$Mergers_{i,z,0406}$	Sum of branch deposits of merged institutions as a fraction of all lenders' deposits in a ZIP code z;
$LoanAmount(000s)$	The amount of the covered loan, in thousands of US dollars	$Minority$	Dummy variable taking a value of one if the borrower applicant is reported in HMDA data as Asian, Hispanic or Black; zero otherwise;
$Female$	Dummy variable, taking a value of one if the applicant is a female; zero otherwise;	LC_s	Standardized Liquidation Costs index, calculated as the Fannie Mae's reported attorney and notary fees that a lender must pay for starting a foreclosure process in state s;
$Jumbo$	Dummy variable, taking a value of one if the mortgage application is a jumbo loan, zero otherwise;	$Recourse_s$	Dummy variable, taking a value of one if the house serving as collateral for the mortgage application is in a Recourse state s; zero otherwise;
$TotAssets_{i,0406}$	Lender Total Assets (in Billion), average across 2004-2006 (source: HMDA)	$Retained_{i,n,0710}$	Dummy variable, taking a value of one if lender i retains in her balance sheet a mortgage origination, and zero if the mortgage is either rejected or accepted and later securitized (to private investors or GSEs);

This table shows the definition of each variable used in the empirical analysis.

Table 2: Summary statistics

	Panel A: Main sample					
	Source	Mean	Std.Dev.	P5	P95	Observ.
$\text{Approval}_{i,n,0710}$	HMDA	.8618	.3451	0	1	3,875,594
$\text{RetentionShare}_{i,n,0406}$	HMDA	.0246	.0323	.0019	.0769	3,875,594
$\text{HHI}_{(i),n,0406}$	HMDA	.0129	.0133	.0049	.0291	3,875,594
$\text{wDissimilarity}_{i,n,0406}$	HMDA	.0450	.0680	.00095	.1803	3,875,594
Loan Amount (000s)	HMDA	195.73	101.61	70	410	3,875,594
Minority	HMDA	.1526	.3596	0	1	3,875,594
Female	HMDA	.3127	.4636	0	1	3,875,594
Jumbo	HMDA	.0160	.1255	0	1	3,875,594
Loan-to-Income (LTI)	HMDA	2.622	1.146	.929	4.600	3,875,594
LC_s	Fannie Mae	.6744	.2260	.4286	1	3,875,594

	Panel B: Further analysis					
	Source	Mean	Std.Dev.	P5	P95	Observ.
$\text{Mergers}_{i,0406}$	FRB Chicago & SoD	.0375	.1163	0	.2656	3,875,594
LTI Dummy (=1 if LTI$\geq LTI_{C,t}$)	HMDA	.5257	.4993	0	1	3,875,594
$\text{NewHous}_{n,0710}$	BPS	.0567	.1129	0	.259	1,012,211
$\text{NewHous}_{n,0710}$ (=1 if NH$\geq NH_{C,t}$)	BPS	.225	.417	0	1	1,012,211
Recourse dummy	Ghent and Kudlyak (2011)	.7734	.4186	0	1	3,875,594
$\text{WeaknessQ}_i, 0406$	CR & TFR	1.87	1.23	1	4	2,957,241
$\text{Approval}_{i,n,1114}$	HMDA	.8630	.3438	0	1	1,924,446
$\text{TotAssets}_{i,0406}$ (Billion, \$)	HMDA	1.990	2.780	10	8.570	3,875,594
$\text{HighCost}_{i,n,0710}$	HMDA	.0657	.2440	0	1	3,065,783
$\text{Origination}_{i,n,0710}$	HMDA	.8513	.3557	0	1	3,601,794
$\text{Retained}_{i,n,0710}$	HMDA	.2760	.4470	0	1	3,601,794

Note: This table shows the source and summary statistics (average, standard deviation, 5th and 95th percentile, and number of observations) for the variables used in the application-level analysis. HMDA stands for "Home Mortgage Disclosure Act" data; BPS for the "Building Permit Survey"; FRB and SoD for "Federal Reserve Bank" and "Summary of Deposits", respectively; CR and TFR for "Call Reports" and "Thrift Financial Report". For variable definitions see Table 1.

Table 3: Fire-sale Risk and Mortgage Approval

Dep. variable: Approval	(1)	(2)	(3)	(4)	(5)	(6)
RetShare	.259***	.434***	.339***	.679***	.345***	.696***
	(.0123)	(.0382)	(.0159)	(.0445)	(.0162)	(.0449)
$\text{HHI}_{(i)}$			.838***	2.709***	.838***	2.688***
			(.119)	(.366)	(.119)	(.366)
wDissimilarity					.108***	.299***
					(.0264)	(.0843)
RetShare $\times LC_s$		-.243***		-.459***		-.474***
		(.0498)		(.0581)		(.0588)
$\text{HHI}_{(i)} \times LC_s$				-2.477***		-2.422***
				(.476)		(.476)
wDissimilarity $\times LC_s$						-.283**
						(.120)
Borrowers' controls	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Neighborhood FE	✓	✓	✓	✓	✓	✓
# of Observations	3,875,594	3,875,594	3,875,594	3,875,594	3,875,594	3,875,594
R^2	.121	.121	.121	.121	.121	.121
adj. R^2	.109	.109	.109	.109	.109	.109

Note: This table presents application-level OLS estimates for the effect of the fire-sale risk on the probability to accept a mortgage application. $Approval_{i,n,0710}$ is a dummy variable taking value of one if a lender i accepts over 2007-2010 a mortgage application in neighborhood n, and zero otherwise. Proxies for (decreasing) fire-sale risk are: $RetShare_{i,n,0406}$, calculated as the number of lender i's retained mortgages as a fraction of total mortgages in neighborhood n over 2004-2006; $HHI_{(i),n,0406}$ as the sum of squared retention share of all lenders in n, except for lender i's, and $wDissimilarity_{i,n,0406}$, as the euclidean distance of retained-portfolio mortgages between a lender i and all other lenders in neighborhood n. State s fixed regulatory costs of foreclosure are denoted with LC_s ($\in [0,1]$). Borrowers' controls (loan-to-income, loan amount, race, gender, jumbo cutoff) and lender (5,079), neighborhood (48,633) and year (4) fixed effects are included in all specifications. ZIP code-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For variable definitions see Table 1.

Table 4: Instrumental variable estimation

	First stage		2SLS	
Dep. variables:	RetShare	RetShare $\times LC_s$	Approval	
	(1)	(2)	(3)	(4)
Mergers	-.0198***	-.0349***		
	(.0038)	(.00319)		
Mergers $\times LC_s$	.0847***	.0968***		
	(.00705)	(.00656)		
RetShare			2.392***	2.614***
			(.376)	(.400)
$\text{HHI}_{(i)}$				10.25***
				(1.719)
wDissimilarity				1.041***
				(.165)
RetShare $\times LC_s$			-2.274***	-3.084***
			(.437)	(.468)
$\text{HHI}_{(i)} \times LC_s$				-12.33***
				(1.961)
wDissimilarity $\times LC_s$				-1.362***
				(.217)
Borrowers' controls	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Neighborhood FE	✓	✓	✓	✓
# of Observations	3,875,594	3,875,594	3,875,594	3,875,594
R^2	.610	.634	.005	.005
Kleibergen Wald F-stat			118.5	155.4

Note: The table presents the results of a 2SLS analysis exploiting mergers among large banks ($\geq \$1billion$ in assets). The instrumenting variable $Mergers_{i,z,0406}$ sum merged institutions' deposits as a fraction of total deposits within a ZIP code. LC_s is the state s fixed liquidation cost index. The first two columns of the table show the first stage results. The second stage estimates the effect of instrumented $RetShare_{i,n,0406}$ and $RetShare_{i,n,0406} \times LC_S$ (column 3), as well as with other (non-instrumented) fire-sale risk proxies (column 4), on approval probability, $Appr_{i,n,0710}$. ZIP code-clustered standard errors in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For variable definitions see Table 1.

Table 5: fire-sale risk versus propping-up

Dep variable: Approval							
	Panel A: New housing				Panel B: Riskier borrowers		
	(1)	(2)	(3)		(4)	(5)	(6)
RetShare	.336***	.351***	.335***	RetShare	.345***	.306***	.299***
	(.0264)	(.0282)	(.0280)		(.0162)	(.0236)	(.0170)
$\text{HHI}_{(i)}$	.943***	.930***	.880***	$\text{HHI}_{(i)}$	.838***	.819***	.647***
	(.149)	(.153)	(.158)		(.119)	(.125)	(.116)
wDissim	.133***	.129***	.131***	wDissimilarity	.108***	.105***	.0846***
	(.0349)	(.0354)	(.0357)		(.0264)	(.0274)	(.0266)
RetSh $\times NewHous$		-.136	-.0017	RetSh $\times LTI$		.0153***	.0902***
		(.149)	(.0269)			(.0069)	(.0124)
$\text{HHI}_{(i)} \times NewHous$		1.432**	.0988	$\text{HHI}_{(i)} \times LTI$		.0022	.0373***
		(.557)	(.0916)			(.0162)	(.0371)
wDissim $\times NewHous$		.027	.0062	wDissim $\times LTI$		.0001	.0378***
		(.157)	(.0136)			(.0033)	(.0054)
Borrowers' controls	✓	✓	✓		✓	✓	✓
Lender FE	✓	✓	✓		✓	✓	✓
Year FE	✓	✓	✓		✓	✓	✓
Neighborhood FE	✓	✓	✓		✓	✓	✓
# of Observations	1,025,395	1,011,508	1,011,508		3,875,594	3,875,594	3,875,594
R^2	.105	.100	.104		.121	.121	.122

Note: The table presents two tests to distinguish the fire-sale risk channel from the *propping-up* conjecture. Panel A includes applications for house purchases in neighborhoods with new construction. In column 2, $NewHous_{n,t}$ is the fraction of the number of houses newly built and the housing stock in neighborhood n. In column 3, $NewHous_{n,t}$ takes value of 1 when the ratio is higher than the county-year average. Panel B shows specifications that include the interaction of fire-sale proxies with the borrower Loan-to-Income (LTI). In column 5, LTI is the continuous version of this variable, while in column 6, it takes the value of 1 when LTI is higher than the county-year average. ZIP code-clustered standard errors are in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For variable definitions see Table 1.

Table 6: Robustness tests

Dep. variable:	Approval				
Sub-sample:	Recourse (1)	WeakL (2)	RiskyB (3)	2ndLien (4)	LenderSize (5)
RetShare	.850***	1.156***	.758***	1.390***	.650***
	(.056)	(.072)	(.061)	(.161)	(.0449)
$\text{HHI}_{(i)}$	2.981***	5.70***	3.144***	1.877	2.477***
	(.443)	(.690)	(.491)	(1.36)	(.362)
wDissimilarity	.381***	2.067***	.344***	.650	.287***
	(.109)	(.776)	(.127)	(.598)	(.084)
RetShare $\times LC_s$	-.679***	-1.013***	-.525***	-1.008***	-.410***
	(.068)	(.088)	(.079)	(.232)	(.059)
$\text{HHI}_{(i)} \times LC_s$	-2.843***	-5.810***	-2.940***	.732	-2.151***
	(.545)	(.875)	(.613)	(2.082)	(.472)
wDissim $\times LC_s$	-.399***	-2.335*	-.307*	-.766	-.266**
	(.149)	(1.28)	(.184)	(1.07)	(.120)
$\text{Size}_i \times LC_s$					-.000042***
					(.0000044)
Borrowers' controls	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Neighborhood FE	✓	✓	✓	✓	✓
# of Observations	2,997,351	1,805,874	2,036,022	230,060	3,875,594
R^2	.125	.098	.144	.267	.122

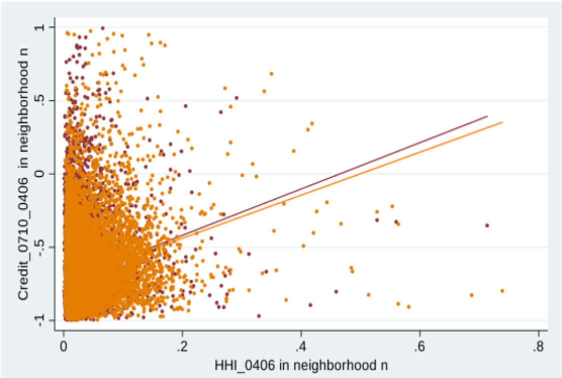
Note: This table presents application-level OLS estimates keeping the same structure of the baseline model (Table 3, column 6), yet focusing on different sub-samples (columns 1-4) or adding a new control variable (column 5). In column 1, we focus on applications in recourse states; in column 2, only on weak lenders (i.e., those with a capital ratio in the lowest quartile of the nationwide lender type-distribution); column 3 explores the fire-sale risk effects on applicants with an LTI larger than the annual county average; column 4 takes the subset of second-lien and no-lien applications; in column 5, $Size$ or $TotalAssets_i \times LC_s$ is appended to the baseline specification. ZIP code-clustered standard errors in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For variable definitions see Table 1.

Table 7: Further analysis

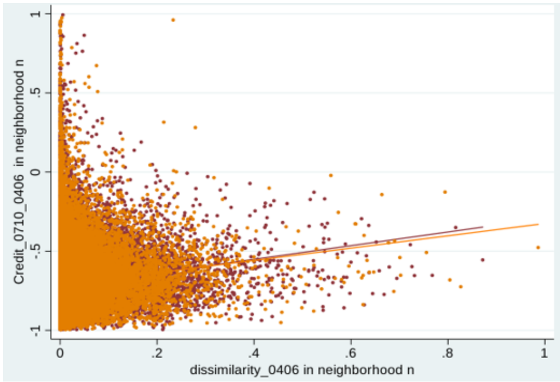
Dep. variable:	Approval_{07} (1)	Approval_{1114} (2)	HighCost (3)	Origination (4)	Retained (5)
RetShare	.792***	.505***	-.348***	.719***	1.259***
	(.067)	(.068)	(.034)	(.048)	(.065)
$\text{HHI}_{(i)}$	2.679***	2.305***	-1.329***	2.907***	3.067***
	(.538)	(.473)	(.284)	(.397)	(.471)
wDissimilarity	.500***	-.072	-.151	.285***	.307***
	(.141)	(.099)	(.095)	(.089)	(.105)
RetShare $\times LC_s$	-.545***	-.229***	.264***	-.419***	-.986***
	(.092)	(.087)	(.040)	(.063)	(.090)
$\text{HHI}_{(i)} \times LC_s$	-2.105***	-2.017***	1.111***	-2.463***	-2.822***
	(.728)	(.570)	(.320)	(.509)	(.616)
wDissim $\times LC_s$	-.506**	.202	.0086	-.232*	-.354**
	(.200)	(.141)	(.134)	(.126)	(.154)
Borrowers' controls	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Neighborhood FE	✓	✓	✓	✓	✓
# of Observations	1,493,004	1,922,631	3,065,783	3,601,794	3,601,794
R^2	.183	.113	.226	.133	.355

Note: This table presents application-level OLS estimates keeping the same structure of the baseline model (Table 3, column 6), yet replacing the dependent variable. In column 1 and 2, we examine lender approval decisions in 2007 and 2011-2014, respectively. In column 3, the baseline $Appr_{i,n,0710}$ gets replaced by mortgage interest rates, $HighCost_{i,n,0710}$, which takes value of one if the interest rate charged on accepted loans is higher than a comparable Treasury rate; column 4 explores the fire-sale risk effects on origination outcomes, $Orig_{i,n,0710}$, taking value of one if the mortgage application is accepted by the lender and the contract is accepted by the borrower; zero otherwise. The last column replaces the previous dependent variable with $Retained_{0710}$, which takes the value of one if the lender accepts *and* retains in her balance sheet the mortgage loan, and zero if it is rejected *or* securitized (to private investors or GSEs). ZIP code-clustered standard errors in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For variable definitions see Table 1.

Figures



(a) Concentration and Credit Volume Changes



(b) Portfolio Dissimilarity and Credit Volume Changes

Figure 1: Macro Evidence. The figure plots changes in Credit Volumes (on the y-axis) against fire-sale risk (on the x-axis). The concentration (Herfindahl-Hirschman) Index HHI (in figure 1a) is calculated at neighborhood n level first, and aggregated at state level using the relative credit volume in each neighborhood. Portfolio orthogonality (in figure 1b) is at lender i-neighborhood n level and it is first aggregated at the neighborhood n using the local retention shares of the lenders, and then at the state level using the relative credit volume in each neighborhood. Orange (Red) dots and regression lines refer to states with foreclosure costs above (below) the average value across all states .

Appendix

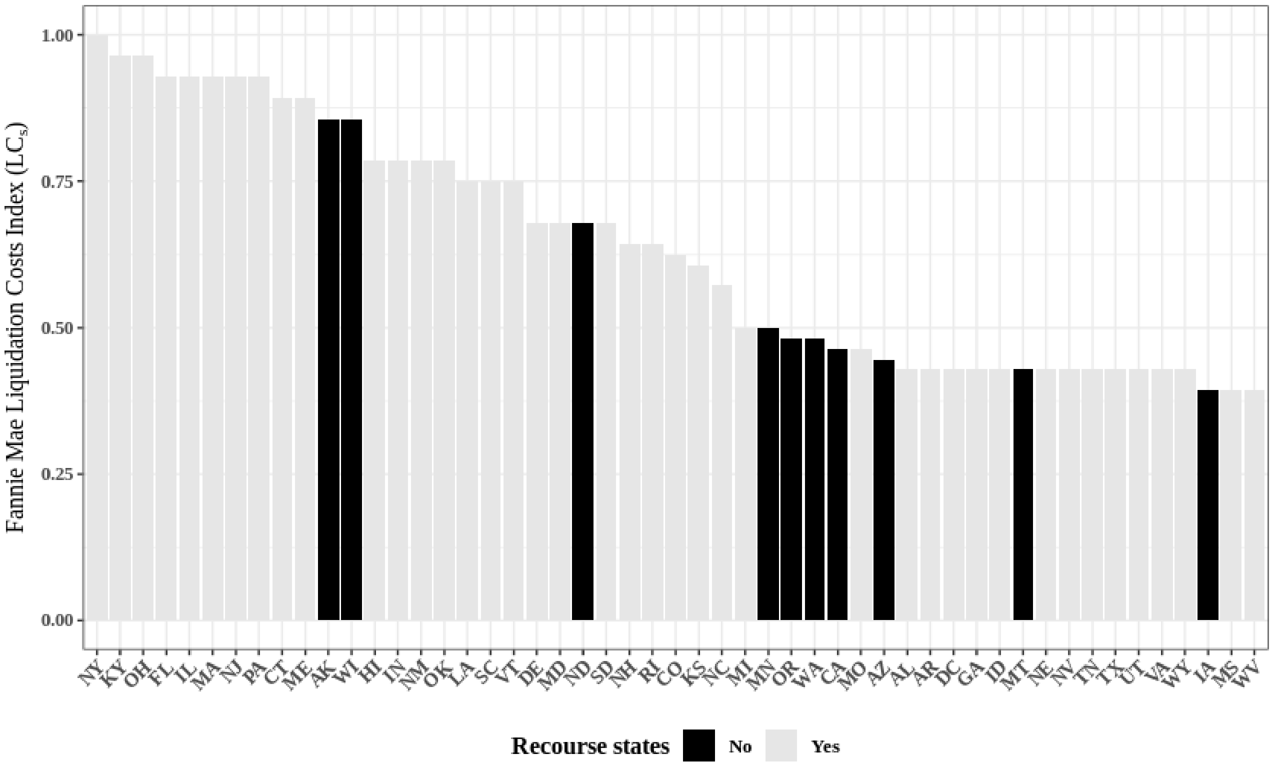


Figure 2: Fannie Mae US Foreclosure Costs Index. This figure plots the foreclosure attorney's and trustee's fees per state - deflated by the most expensive one - that we use in our regressions. Black (white) bars indicate states without (with) recourse clause.

Table 8: Annual HMDA mortgage applications by lender type, 2007-2010

	2007	**2008**	**2009**	**2010**
***Panel A**: Number of applications by lender type*				
Commercial banks	1,224,357	711,929	560,969	495,132
Thrifts	364,941	234,136	111,381	75,737
Credit Unions	44,997	41,035	35,537	33,438
Independent Mortgage Companies	257,553	134,685	108,197	88,749
***Panel B**: Number of distinct lenders by type*				
Commercial banks	2,840	2,691	2,541	2,377
Thrifts	487	472	420	400
Credit Unions	1,088	1,071	983	979
Independent Mortgage Companies	592	456	406	340
***Panel C**: Number of distinct neighborhoods by lender type*				
Commercial banks	48,199	46,430	44,625	44,024
Thrifts	41,358	37,779	28,186	21,079
Credit Unions	13,923	13,356	11,758	11,621
Independent Mortgage Companies	35,331	27,748	23,341	20,814

Note: This table shows aggregated figures of HMDA mortgage applications per lender type over time. Source: HMDA.

A Loan origination incentives and market structure

We consider a bank that has a market share of s_1 in its local lending market. The residual market consists of another (large) bank and a set of small atomistic banks. Their respective market shares of the residual market are $\widetilde{s}_2$ and $1 - \widetilde{s}_2$ (which is equivalent to market shares of $s_2 = (1 - s_1)\widetilde{s}_2$ and $s_3 = (1 - s_1)(1 - \widetilde{s}_2)$ of the whole market).

Banks originate loans at date 0 which mature at date 2. At date 1, with probability p all loans in the market become troubled (this is for simplicity, the qualitative results are unchanged if only a fraction of loans becomes impaired). A bank can decide to renegotiate impaired loans. This will incur a fixed loss of k per loan to the bank due to lower payments from the borrower. A bank can also repossess the house and sell it in a foreclosure process. In this case there are fire-sale costs c, which are assumed to be increasing in the *total* amount of loans being foreclosed in the market. Specifically, we assume that

$$c = c_0 l, \tag{2}$$

where l is the total number of housed being sold. Banks are assumed to play *Cournot* strategies in the liquidation market, by deciding on the amount of loans to foreclose (with the rest being renegotiated).

We will analyze how a bank's own market share (captured by s_1) and concentration in the residual market (captured by $\widetilde{s}_2$) affects the incentives to originate a loan. Note that the definition of own and residual concentration is consistent with our variable definitions in Section 3.1.

We solve the model backwards, starting with the date-1 foreclosure market.

A.1 Date-1 foreclosure decisions

Atomistic banks will take liquidation prices as given. They will therefore foreclose ("liquidate") all their loans if the prevailing liquidation prices are less than the restructuring cost.

This is the case when

$$c_0(1 - s_1)(1 - \widetilde{s}_2) < k. \tag{3}$$

We assume this condition to be fulfilled, such that all atomistic banks foreclose all their loans in a crisis. Under this assumption, liquidation costs in this market are given by

$$c = c_0(l_1 + l_2 + (1 - s_1)(1 - \widetilde{s}_2)), \tag{4}$$

where l_1 and l_2 are the liquidation amounts of the two large banks.

The two large banks each minimize their respective costs associated with impaired loans, f_1 and f_2:

$$f_1 = l_1 c + (s_1 - l_1)k, \tag{5}$$

$$f_2 = l_2 c + (s_2 - l_2)k. \tag{6}$$

Taking the liquidation quantity of the other bank as given, the optimization problems become respectively:

$$l_1^* = \arg\min_{l_1} f_1(l_{1,} l_2) \text{ and } l_2^* = \arg\min_{l_2} f_2(l_1, l_2). \tag{7}$$

The resulting equilibrium quantities are:

$$l_1^* = l_2^* = \frac{\frac{k}{c0} - (1 - s_1)(1 - \widetilde{s}_2)}{3} \tag{8}$$

A.2 Date-0 loan origination

We now analyze how the incentives to originate an additional loan depend on a bank's own market s_1 and residual market concentration $\widetilde{s}_2$. For a given lending rate r, profits of the bank are

$$\pi = s_1 r - pf. \tag{9}$$

The marginal profitability of a (new) loan is hence given by

$$\pi'(s_1) = r - pf'(s_1), \tag{10}$$

and determined by the marginal liquidation cost, $f'(s_1)$. The latter consist of three parts (we can ignore the effect coming through adjustment in l_1 because of the envelop theorem):

$$f'(s_1) = k - l_1^* c_0(1 - \widetilde{s}_2) + l_1^* c_0 l_2^{*\prime}(s_1) = k - \frac{2}{3} l_1^* c_0(1 - \widetilde{s}_2). \tag{11}$$

The first effect, k, simply arises because when there are more loans, liquidation costs (expressed in absolute terms) are higher. The second effect, $-l_1^* c_0(1 - \widetilde{s}_2)$, arises because more loans increase the market share of the bank. There are hence fewer atomistic sellers, which lowers liquidation costs. The third effect, $l_1^* c_0 l_2^{*\prime}(s_1)$, partially offsets this second effect, because the other bank will also expand its liquidations, thereby lowering liquidation prices.

We next consider how the marginal profitability of (additional) lending is affected by the own market share. For this we take derivative of the marginal profits with respect to s_1 (again) to obtain

$$\pi''(s_1) = -pf''(s_1). \tag{12}$$

The direction of the effect thus depends on the second derivative of the liquidation costs. From Equation (11) we have

$$f''(s_1) = -\frac{2}{3} c_0 l_1^{*\prime}(s_1)(1 - \widetilde{s}_2) = -\frac{2}{9} c_0 (1 - \widetilde{s}_2)^2 < 0. \tag{13}$$

It follows that $\pi''(s_1) > 0$. The intuition is the following: when a bank has a high market share, it liquidates a large number of loans (both in absolute terms, but also relative to its portfolio). It therefore benefits more when liquidation prices improve due to higher market power (which is achieved through increasing its market share).

Finally we turn to the effect of residual market concentration on the incentives to originate loans. Taking the derivative of the marginal profitability of lending with respect to $\widetilde{s}_2$ we obtain

$$\frac{d\pi'(s_1)}{d\widetilde{s}_2} = -p\frac{df'(s_1)}{d\widetilde{s}_2}. \tag{14}$$

We have for the cross-derivative of the liquidation costs

$$\frac{df'(s_1)}{ds_2} = -\frac{2}{3}c_0(l_1^{*\prime}(\widetilde{s}_2)(1-\widetilde{s}_2) - l_1^*) = -\frac{2}{9}c_0\frac{2s_3 - \frac{k}{c0}}{3}. \tag{15}$$

This expression will be negative (and hence $\frac{d\pi'(s_1)}{d\widetilde{s}_2}$ positive) as long as overall market dispersion (measured by the share of small banks in the market, s_3) is sufficiently large. The intuition is similar to the previous one. When a bank has higher market power, it liquidates a larger amount of loans, and hence benefits more from higher liquidation prices that result when the residual market becomes more concentrated.

Note that the functional forms of $f''(s_1)$ and $\frac{df'(s_1)}{ds_2}$ (and hence $\pi''(s_1)$ and $\frac{d\pi'(s_1)}{d\widetilde{s}_2}$) differ. This means that the coefficients on s_1 and $\widetilde{s}_2$ can be identified even from within-market variation.

A.3 Credit allocation across markets

Suppose that we now have two markets, one with high concentration H and one with low concentration L. Specifically, lets assume that the market shares of bank 1 and bank 2 in market H is higher than in market L ($s_1^H > s_1^L$ and $s_2^H > s_2^L$). Denote the share of loans in the economy extended in market H and L with w_H and $w_L = 1 - w_H$, respectively. Assume further that the (per loan) fire-sale discount c is independent of market size w, the idea being that in larger markets there is both more supply of houses in a foreclosure, but also a larger set of potential buyers. Total fire-sale costs (per unit of loans extended) in the economy are given by

$$C = w^H f^H + (1 - w^H) f^L, \tag{16}$$

where $f^H := f_1^H + f_2^H + (1 - s_1^H - s_2^H)f_3^H$ and $f^L := f_1^L + f_2^L + (1 - s_1^L - s_2^L)f_3^L$ are the total (per-loan) fire-sale costs in the high and low market, respectively.

Consider now a reallocation of credit from neighborhood L to neighborhood H, which preserves the market shares in each neighborhood. From Equation (16) we have that $C'(w^H) = f^H - f^L$. In addition we have that $f'(s_1) < 0$ and $f'(s_2) < 0$, from which it follows that $f^H < f^L$. Hence we have that $C'(w^H) < 0$.