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JEL Classification: N/A

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

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DION BONGAERTS, FRANCESCO MAZZOLA and WOLF WAGNER*

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This paper examines whether the risk of a future collateral fire sale affects lending decisions. We study US mortgage applications and exploit exogenous variation in foreclosure frictions for identification. We find lenders to be 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. These results suggest that fire-sale risk has implications for credit allocation, and that lenders' collective origination decisions mitigate fire sale risk ex-post. However, we also find the effects to be significantly weaker outside periods in which fire sales are salient.

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1 Introduction

Prematurely liquidated assets may trade at dislocated—or fire sale—prices since investors have incentives to sell troubled assets quickly, while potential buyers are liquidity-constrained (Williamson, 1988; 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 internalization could in principle mitigate ex-post fire sale risk. These are important questions since fire sales can result in large costs, for individual investors, but also at the systemic level as they exacerbate economy-wide credit constraints and result in feedback loops.

This paper uses the U.S. mortgage market as a laboratory to study the consequences of fire sale risk. The advantage of using this market is that it consists of many different local liquidation markets (i.e., neighborhoods) with each relatively homogeneous assets (i.e., residential dwellings). Houses are collateral assets that, under a foreclosure process, lenders can repossess and liquidate, typically at a price well below market value (Campbell et al., 2011; Anenberg and Kung, 2014; Ramcharan, 2020). Using comprehensive micro-level data, our paper shows that mortgage credit is reduced in markets where the anticipated losses from foreclosure sell-offs 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 costs are expected to be lower in markets with higher lender concentration. Lenders with a large share of local debt are more likely to internalize negative spillovers when deciding to foreclose a mortgage (Favara and Giannetti, 2017, provide empirical evidence for this). 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, where atomistic lenders may want to "rush to the exit" (Oehmke, 2014), creating strategic complementarities in liquidation decisions. We thus

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

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 overall dispersion of market shares. Second, fire sales are more likely, and expected to be more severe, when locally active lenders 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 thus prefer originating credit in a market with more dissimilar lenders (Wagner, 2011).

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. Since these variables may affect credit supply also through other channels (e.g., a high market share may indicate operational synergies), we obtain identification from interacting these variables with state-level legal foreclosure frictions.[2] We hypothesize both channels to be weaker when these frictions are high, as foreclosures, and hence fire sales, are then less relevant. To minimize the scope for unobserved heterogeneity, we base our analysis on granular application-level data and saturate our models with fixed effects. We focus on the period of the Global Financial Crisis for our baseline analysis. During this period foreclosures are salient (Gupta, 2016; Mian et al., 2015); in addition, the markets for private securitization 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 either proxy of fire sale risk lowers the acceptance rate by around 1 percentage point. Importantly, all three channels are significantly weaker, both in statistical and economic terms, in states with higher fore-

[2]The literature shows that foreclosure laws do not correlate with any state-level economic conditions (Ghent and Kudlyak, 2011), establishing an exogenous treatment that is useful for empirical identification. See figure 2 for the cross-section of state legal costs.

closure frictions. To further mitigate the risk of endogeneity driving our results, 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 plausibly exogenous variation in a lender's market share. The analysis based on instrumental variable estimation confirms, and even strengthens, the baseline results.

Collectively, the results suggest that lenders reduce credit supply in local markets with high fire sale risk. Whereas our main analysis is based on the analysis of individual mortgages, we also perform an exercise to examine 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. This suggests that nationwide fire sale costs, measured per unit of credit, are reduced.

The most similar conjecture to ours is explored in Giannetti and Saidi (2018) and Gupta (2019), who propose that high-market-share banks have incentives to provide liquidity when collateral prices *are already* depressed, as this props up industry-wide collateral prices and benefits their existing lending portfolio (*propping hypothesis* henceforth). By contrast, our conjectures are based on lenders anticipating the risk of future fire sales. We disentangle the two mechanisms by focusing on scenarios in which both channels are unlikely to hold simultaneously. We first analyze loans extended for home construction. Such loans increase local 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 fire sale proxies to affect lending decisions in areas with high construction intensity in a statistically different way. Secondly, we exploit variation in borrower default risk. Borrower default risk is a key driver of fire sale risk, but irrelevant 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" 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 similar to our baseline analysis. Second, we find that fire sale risk has larger effects at lenders with weak balance sheets. 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, thus approval and pricing decisions are consistent. Fourth, we investigate actual credit origination (for a mortgage approval to translate into actual credit, borrowers should not reject the terms offered by the bank) and find the results to be similar to the ones obtained from mortgage approvals. Finally, we find our results to be much weaker outside the Global Financial crisis, consistent with fire sales being much less salient there.

Our study contributes to the literature linking credit supply to collateral fire sales. Several theoretical studies show that, in the presence of transaction costs and contractual incompleteness, the value of the option to liquidate a 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 differences in *sellers*' propensity to liquidate. For identification, we draw on a relatively recent literature that shows that borrower protection laws directly affect recovery values and, consequently, that lenders originate fewer and smaller loans in states where the foreclosure process is more expensive (Pence, 2006; Dagher and Sun, 2016; Milonas, 2017;

Degryse et al., 2020).

We also contribute to the 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), and stifle innovation (Aladwani, 2001). By contrast, our results suggest shows that banking concentration can alleviate credit constraints by reducing the negative effects of fire sales. This effect is distinct from other positive effects of banking concentration, such as greater scope for relationship lending (Petersen and Rajan, 1995) or mitigation of industry-wide shocks (Giannetti and Saidi, 2018).

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, at least during crisis times, since this reduces their exposure to fire sale losses going forward. In that vein, fire sale have a beneficial disciplining effect. This echoes findings in the literature that stress 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 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 and selling the collateral to a third party. The price at which 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 these 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 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 liquidations to identify channels that relate credit supply to fire sale risk, and construct associated empirical proxies.

When a lender forecloses defaulting 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; Ramcharan, 2020). Hence, mortgage foreclosures impose a negative externality on other lenders that plan to foreclose. 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 to foreclose 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 defaulting mortgages ex-post, resulting in lower fire-sale discount per loan. Second, the externality will depend on dispersion in the *rest of the market*. For a given own share, if the other lenders in the market are more concentrated, they will themselves be less inclined to fire sale. This results in lower fire-sale discounts, as shown empirically by Favara and Giannetti (2017). Summing up, lenders are less exposed to fire-sales when their local market share is large, and when the rest of the market is more concentrated. This yields 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 local market (exluding her own share) is more concentrated.*

Predictions 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, when prices are very depressed. 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: lenders can expect low collateral foreclosure prices in local markets with high dispersion. A second reason for low foreclosure prices arises when lenders are forced to collectively liquidate because of joint liquidity or capital needs (that is, when liquidations are also affected by lenders' financial positions, not only borrower default). 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 overlapping portfolios. Wagner (2011) shows theoretically that the gains from investing ex-ante in an asset declines if there is larger commonality with other banks that invest in the same asset, due to higher fire sale risk.[3] 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 risk. To isolate the effects that come from fire sale risk, we exploit frictions in the mortgage foreclosure process. In particular, we focus on examining how the magnitude of the channels underlying Predictions 1 to 3 vary when there are exogenous variations in the feasibility of collateral liquidations. One such source of variation corresponds to state judicial barriers associated with the foreclosure process. These barriers vary widely across states and, importantly, have been found to be unrelated to economic conditions (Ghent and Kudlyak, 2011). If the implied legal costs to foreclose are high, foreclosure is simply not an attractive option, and collateral liquidation prices become irrelevant for lenders. This leads to the following empirical implication:

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

3 Data

Our main data source is the comprehensive dataset made available under the Home Mortgage Disclosure Act (HMDA). It contains detailed information on the full U.S. universe of mortgage applications. This data cover more than 80% of all lenders and 95% of total mortgage volume in urban areas (Dagher and Sun, 2016). Most importantly for our analysis,

[3]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.

individual application records include the lender's decisions (whether to originate, and possibly whether to securitize later) as well as the location of the property. The dataset in addition 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. To minimize the impact of potential outliers, we truncate the 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 institutions. We use the annual locations and deposits 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.

Private securitization is common in the U.S. mortgage market (using structured products, and conduits), which potentially complicates our analysis. For example, the prospect of securitization may affect and thereby contaminate credit origination decisions (e.g., see Berndt and Gupta (2009) for the syndicated corporate loans, and Keys et al. (2010); Dell'Ariccia et al. (2012); Rajan et al. (2015) for the mortgage market). To minimize such issues, we focus in our main analysis on mortgage applications made during the Global Financial Crisis (2007 to 2010). During this period the private securitization market was frozen.[4] We construct fire sale risk proxies using only pre-crisis information, specifically the period of 2004 to 2006, to address the potential for reverse causation.

Since foreclosure spillovers arise within a small geographical radius (Campbell et al., 2011; Ramcharan, 2020), we define a local market at the neighborhood level using the census tract structure.[5] For some of our analyses, we use data that are only available at the

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

[5]A census tract ("neighborhood" in the empirical analysis) is the finest geographical level at which HMDA data can localize a property. It is a small area within a county and generally contains 4,000 inhabitants. Mian et al. (2015) shows that negative price externalities of foreclosures arise also across zip codes, which typically contain several census tracts.

zip-code level. Therefore, we match each neighborhood to zip codes using data from the Missouri Census Data Center.[6] We exclude zip codes with only one lender. We assign each mortgage application received by any affiliate or subsidiary lender to her respective parent company using, when unavailable in HMDA, information from the Federal Reserve's National Information Center (NIC). The types of lenders that need to report their received applications under HMDA consist of commercial banks, thrifts, and mortgage companies.[7] We only consider that originate mortgages in at least two neighborhoods. After applying these standard filters, our main application-level dataset contains nearly 4 millions mortgage applications, made to 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 approval decision to finance mortgage applications for properties in neighborhood n is affected by her own market share in this neighborhood, the concentration of market shares of the other lenders in the neighborhood as well as her portfolio overlap with these lenders. 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:

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

where $RetLoans_{i,n,0406}$ is the number of mortgages that lender i has originated and retained on her balance sheet in neighborhood n and $TotalLoans_{n,0406}$ is the total number of mortgages originated - retained and securitized - of 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 con-

[6]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.

[7]See table 7 in the Appendix for the characteristics of the sample applications per lender type over time.

centration measure of outstanding mortgages $HHI_{(i),n,0406}$. For each lender i we exclude its 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 $\sum_j (RetShare_{j,n,0406})^2$; $TotalLoans_{i,n,0406}$ 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 originated in the neighborhood. The 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 (see e.g., Favara and Giannetti, 2017; Oehmke, 2014). This variable will be used to test Prediction 2. Because $HHI_{(i),n,0406}$ varies across lenders and hence within a neighborhood, it allows for the model to contain 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 portfolio weights between lender i and another lender j

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

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, lenders on average have retained-mortgages in 514 neighborhoods.

$EuclDist_{i,j,0406}$ measures portfolio dissimilarity between lender i and another lender. 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:

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

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).

To examine whether fire sales risk is attenuated by liquidation costs, we complement our application-level dataset with information on foreclosure laws at state-level. We use the most granular measure of state-level foreclosure costs, that is, the Fannie Mae Foreclosure Timeline index. Fannie Mae publicly outlines in their Servicing Guide the main Attorney's and Trustee's fees governing each state (in U.S. dollar terms). 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, as in Dagher and Sun (2016).[8] To examine Prediction 4 we interact retention shares, residual concentration and portfolio dissimilarity measures with this cost index. We focus our empirical analysis on these interactions, for reasons of identification.

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

[Table 1 here]

Table 1 describes the summary statistics of the variables used throughout the empirical

[8] 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`;

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 equals 0.013. By construction, both $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ averages are small over the full sample, since we scaled retained market shares by the sum of retained *and* securitized mortgages (as in Favara and Giannetti, 2017). This is consistent with the general idea that securitized mortgages are held by passive investors and have foreclosure triggers and procedures following securitization contracts. The portfolio overlap with local competitors is high on average (95.5%). Importantly, all three measures show considerable cross-sectional variation.

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.[9] 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 mortgage application made by borrower m for a house in neighborhood n in year t between 2007 and 2010; $FSR_{i,n,0406}$ 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

[9]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).

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,[10]; finally, $\eta_{i,n,t}$ is a vector of lender, neighborhood, and year fixed effects. Following Predictions 1-3 we expect $\beta_1 > 0$ as lower fire sale risk (that is, larger values for $FSR_{i,n,0406}$) increases lending. The interaction term is expected to be negative ($\beta_2 < 0$) as barriers to foreclosures reduce the relevance of potential fire sales (Prediction 4).

The inclusion of fixed effects absorbs any time-invariant effects that are neighborhood or lender specific, such as foreclosure and mortgage demand, as well as any common trends over time (Petersen and Rajan, 2002; Benmelech et al., 2005). Standard errors are clustered at zip code-level to account for residual correlation at the regional level. Table 2 shows the results of the baseline model of equation (1).

[Table 2 here]

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 fire sales for origination decisions. The third and fourth columns add the residual concentration to the model. These columns show that credit supply (approval rate) increases in the concentration of debt outstanding (larger values of $HHI_{(i),n,0406}$); but do so less in states with large foreclosure costs (negative and significant coefficient on the $HHI_{(i),n,0406} \times LC_s$). Finally, column 5 and 6 add the portfolio overlap channel to the specification. In column 5 we can see that the coefficient on this new variable - as well as on the other channels - is

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

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 the table thus confirm the predictions derived in Section 2. 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).

Since standard errors may be compressed in large samples, it is important to also assess economic significance. In column 3, a one-standard deviation increase 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, 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 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 South Carolina (where LC_s is at 0.75).

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)), aggregated using 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 Dagher and Kazimov, 2015, approach). Consistent with the micro-evidence, we see that lending declines less in concentrated neighborhoods and neighborhoods where lenders have dissimilar portfolios (the slope of the regression lines is positive). Importantly, the slope of the regression line for neighborhoods with high foreclosure costs (red line) is flatter than the corresponding line for low foreclosure costs (orange line), consistent with Prediction 4.[11]

4.1 M&A exogenous shocks

While our identification strategy based on exploiting exogenous variation in legal foreclosure costs goes a long way in ruling out alternative channels, there may still be some residual concerns about endogeneity. In particular, anticipation of low (or high) fire sale risk could affect market conditions ex-ante, thereby leading to reverse causality. To address such effects (or any other sources of endogeneity at the supply side), 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 level of top management, rather than based on considerations at the level of an individual neighborhood, making the exogeneity assumption unlikely to be violated. We identifying 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), we construct a measure of local M&A intensity using bank branch data from the Summary of Deposits:

$$Mergers_{i,z,0406} = \frac{\sum SurvivorBranches_z Deposits}{\sum TotalBranches_z Deposits}$$

where $\sum SurvivorBranches_z Deposits$ 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 zip code. The ratio $Mergers_{i,z,0406}$ denotes the merger intensity (and deposit inflows) of survivor bank i within zip code z. Because of positive deposits shocks, banks can

[11]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 disimilarity index are 2.3 (2.5) percentage points.

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 3.

[Table 3 here]

The first two columns of table 3 show the results of the first stage estimation. As before, we include borrowers' controls and lender, year and neighborhood fixed effects. Higher merger intensity is associated with higher values for $Mergers_{i,z,0406}$ and in turn, should increase $RetShare_{i,n,0406}$. The positive and statistically significant coefficients on the instrumental variables ($Mergers_{(i),z,0406}$ and $Mergers_{(i),z,0406} \times LC_s$) are consistent with these priors. Most importantly, the second stage results (column) are consistent with our earlier results.

Notably, the economic magnitude of the IV analysis is larger than the one of the OLS (table 2, column 6), consistent with Favara and Giannetti (2017). The effects vary almost 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 0.79). An explanation for the higher effects is that instrumenting a local retention share with M&As shocks captures changes in merged banks only. These institutions are likely the ones most efficient, on average. They should also be arguably the entities that have better risk management practices and are hence better able to anticipate fire sale risk.

4.2 The propping-up channel

There is an alternative explanation, also based on fire-sales, for why high market shares make loan origination more attractive (Prediction 1 and 2): once a market is distressed, lenders with larger market shares may have incentives to lend to "prop-up" local house prices. This benefits their existing lending portfolio, by disincentivizing borrowers to strategically default

(Giannetti and Saidi, 2018; Gupta, 2019). In the following we offer two exercises to separate this channel from the fire-sale risk channels (which are ex-ante channels).

We first consider financing of loans for new houses (construction loans). Such loans are undesirable under the propping-up channel, as they increase local housing supply and hence to depress prices (rather than to increase them). By contrast, the fire-sale risk channels equally apply to existing and new houses. The HMDA application data does not, unfortunately, specify whether a specific borrower applies for a mortgage for a newly built property or an existing one. We thus create a measure of home construction intensity at the neighborhood level. We obtain Building Permit Survey data from the U.S. Census Bureau, Manufacturing and Construction.[12] This dataset contains annual residential building permits released at the neighborhood level in all U.S. states. We construct the variable $NewHous_{n,0710}$, ranging from zero to one, as the number of permits for new houses in a census tract n over year t as a fraction of total housing stock therein.

Second, we exploit differences in borrower default risk. Under the *propping-up* channel, the riskiness of the borrower that applies for a loan does not matter, as the 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, defined as the ratio between the loan amount requested and the annual income of the borrower and denoted by LTI_m, to proxy for borrower credit risk.

Table 4 contains the results of both exercises. 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 2).

[Table 4 here]

Panel A contains the analysis of construction intensity. The first column of Table 4 shows

[12] For more information, see https://www.census.gov/construction/bps/.

coefficient estimates for equation (1), keeping the same controls and fixed effects as in the baseline (column 6 of Table 2). Note that the number of applications drop, because BPS neighborhood-level data does not fully match with the HMDA sample. The first column shows that all channels are positive and statistically different from zero. In column 2 and 3, we include interactions with $NewHous_{n,0710}$, on all mortgage applications that BPS offers data for.[13] Coefficients on $RetShare_{i,n,0406}$, $HHI_{(i),n,0406}$ and $wDissimilarity_{i,n,0406}$ are still positive and statistically significant. The interacted versions are not 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 (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). We obtain similar results if we change the definition of construction intensity in column 3, $NewHous_{n,0710}$ equals one if the number of houses newly built in neighborhood n is higher than the county-average in a year and zero otherwise. The coefficient estimates on the interaction terms are all statistically insignificant. The analysis of mortgage acceptances across areas with differing construction activities is thus consistent with fire sale risks, but not with the propping-up channel.

In panel B we examine borrower default risk. Column 4 serves as benchmark. In column 5, we include interaction terms of LTI_m with all three fire sale risk proxies. We find that only $RetShare_{i,n,0406}$ channel increases in the interacted terms. However, this may be due to imperfect measure of credit risk, as credit standards may 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 county-average in a year (as $NewHous_{n,0710}$ dummy in column 3). In this case, all coefficients on the interaction terms are positive and statistically significant. This is consistent with higher fire sale risk in the case of riskier borrowers. Again, the analysis fails to provide support for the *propping-up* channel.

[13]More than 1 million applications coming from nearly 15 thousand distinct neighborhoods.

4.3 Further analyses

Negative home equity represents an important source of household strategic 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 exercise conducted in the baseline equation (1) for a sub-sample of states with recourse laws only (41 out of 51 states, see figure 2 in the Appendix). In these states (orthogonal to judicial costs, 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. The results are shown in table 5.

[Table 5 here]

The first specification in Table 5 confirms our earlier results (estimates are even slightly larger).

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 and face different regulatory regimes (our data includes commercial banks, credit unions and thrifts) we create this measure conditional on lender type. Specifically, we consider from each lender type (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 joint liquidation risk being directly driven by lender health (Wagner, 2011).

In column 3, we do a sub-sample analysis on riskiest borrowers. These are defined as the borrowers with an LTI higher than the county-year average (similarly to column 6 in table 4). The coefficients increase in magnitude with respect to the baseline, suggesting that lenders 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 the decision to foreclose may not be with the lender (in particular so if she is not also the first-lien lender), whereas for unsecured lending collateral is irrelevant. We would thus expect our fire-sale risk channels to be weaker for these type of applications. Column 4 shows that all fire sale risk proxies are now insignificant, except the retention share $RetShare_{i,n,0406}$. A possible explanation for the significant effect 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.

So far we have analyzed fire sale risk *during* the GFC, arguably when fire sale risk was most salient for lenders. We next examine whether fire sale risk also affects lending decisions after the crisis period. We would expect the results to weaken, for several reasons. Loans extended outside the crisis are likely to be safer, hence less likely to be collectively foreclosed, resulting in fewer fire sales (Lorenzoni, 2008; Bianchi, 2011; Mendoza, 2010). Additionally, lenders are likely to be in better health, and hence joint liquidation risk is no longer elevated. Lastly, fire sales may simply be less salient for lenders, and hence affect lending decisions less (Gennaioli et al., 2012). Fifth, post crisis securitization markets were operative again, allowing lenders to pass through mortgages with high fire sale risk.

Column 5 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 better health post-crisis, making joint liquidation less likely.

We next examine whether fire sale risk also affects mortgage rates. Conditional on accepting a mortgage, lenders should require higher compensation if 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.[14] We re-estimate equation (1), replacing the dependent variable with the high-price dummy $HighPriced_{i,n,0710}$, which equals one if the spread with a US treasury of similar maturity is strictly positive and zero otherwise. The coefficients on $RetShare_{i,n,0406}$ and $HHI_{(i),n,0406}$ in column 6 are negative and statistical significant, as well as their interaction effects. The respective signs suggest that lenders require lower interest rates when fire sale is less pronounced.

Lastly, we consider actual loan originations. A loan is only orginated if subsequent to mortgage approval by the lender, the borrower also approves the loan. Mortgage approvals (by lenders) may not translate into new credit if borrowers reject offers due to unfavorable mortgage terms. We thus replace $Approved_{i,n,0710}$ by $Orig_{i,n,0710}$ as 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. Results in column 7 suggest are very similar to our baseline results in column 6 of Table 2.

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

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 the fire sale risk proxies affect credit supply by lowering acceptance rates on mortgage applications. We also show that the effects decrease in states where legal foreclosure costs are higher, strengthening identification. An analysis of mortgage interest rate provide 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 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 fire sale risk, rather than focusing solely on addressing ex-post inefficiencies from fire sales (time inconsistency problem, as in Chari and Kehoe, 2016).

References

Acharya, V. V., Shin, H. S., and Yorulmazer, T. (2011). Crisis Resolution and Bank Liquidity. *Review of Financial Studies*, 24(6):2166–2205.

Acharya, V. V. and Yorulmazer, T. (2007). Too many to fail—an analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, 16(1):1–31.

Acharya, V. V. and Yorulmazer, T. (2008). Information contagion and bank herding. *Journal of money, credit and Banking*, 40(1):215–231.

Aladwani, A. M. (2001). Online banking: a field study of drivers, development challenges, and expectations. *International Journal of Information Management*, 21(3):213–225.

Anenberg, E. and Kung, E. (2014). Estimates of the size and source of price declines due to nearby foreclosures. *American Economic Review*, 104(8):2527–51.

Benmelech, E. and Bergman, N. K. (2009). Collateral pricing. *Journal of Financial Economics*, 91(3):339–360.

Benmelech, E., Garmaise, M. J., and Moskowitz, T. J. (2005). Do liquidation values affect financial contracts? evidence from commercial loan contracts and zoning regulation. *Quarterly Journal of Economics*, 120(3):1121–1154.

Bernardo, A. E. and Welch, I. (2004). Liquidity and financial market runs. *Quarterly Journal of Economics*, 119(1):135–158.

Berndt, A. and Gupta, A. (2009). Moral hazard and adverse selection in the originate-to-distribute model of bank credit. *Journal of Monetary Economics*, 56(5):725–743.

Bianchi, J. (2011). Overborrowing and systemic externalities in the business cycle. *American Economic Review*, 101(7):3400–3426.

Bolton, P. and Scharfstein, D. S. (1996). Optimal debt structure and the number of creditors. *Journal of Political Economy*, 104(1):1–25.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, 23(1):77–100.

Campbell, J. Y., Giglio, S., and Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, 101(5):2108–31.

Cella, C., Ellul, A., and Giannetti, M. (2013). Investors' horizons and the amplification of market shocks. *Review of Financial Studies*, 26(7):1607–1648.

Chari, V. V. and Kehoe, P. J. (2016). Bailouts, time inconsistency, and optimal regulation: A macroeconomic view. *American Economic Review*, 106(9):2458–93.

Dagher, J. and Kazimov, K. (2015). Banks liability structure and mortgage lending during the financial crisis. *Journal of Financial Economics*, 116(3):565–582.

Dagher, J. and Sun, Y. (2016). Borrower protection and the supply of credit: Evidence from foreclosure laws. *Journal of Financial Economics*, 121(1):195–209.

Degryse, H., Ioannidou, V., Liberti, J. M., and Sturgess, J. (2020). How do laws and institutions affect recovery rates for collateral? *Review of Corporate Finance Studies*, 9(1):1–43.

Dell'Ariccia, G., Igan, D., and Laeven, L. U. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. *Journal of Money, Credit and Banking*, 44(2-3):367–384.

Demirci, I., Gurun, U. G., and Yönder, E. (2020). Shuffling through the bargain bin: Real-estate holdings of public firms. *Review of Finance*, 24(3):647–675.

Demiroglu, C., Dudley, E., and James, C. M. (2014). State foreclosure laws and the incidence of mortgage default. *Journal of Law and Economics*, 57(1):225–280.

Farhi, E. and Tirole, J. (2012). Collective moral hazard, maturity mismatch, and systemic bailouts. *American Economic Review*, 102(1):60–93.

Favara, G. and Giannetti, M. (2017). Forced asset sales and the concentration of outstanding debt: evidence from the mortgage market. *Journal of Finance*, 72(3):1081–1118.

Garmaise, M. J. and Moskowitz, T. J. (2006). Bank mergers and crime: The real and social effects of credit market competition. *Journal of Finance*, 61(2):495–538.

Gennaioli, N., Shleifer, A., and Vishny, R. (2012). Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics*, 104(3):452–468.

Georg, C.-P., Pierret, D., and Steffen, S. (2019). Similar investors. *Available at SSRN 3250826.*

Gerardi, K., Herkenhoff, K. F., Ohanian, L. E., and Willen, P. S. (2017). Can't pay or won't pay? unemployment, negative equity, and strategic default. *Review of Financial Studies*, 31(3):1098–1131.

Ghent, A. C. and Kudlyak, M. (2011). Recourse and residential mortgage default: evidence from us states. *Review of Financial Studies*, 24(9):3139–3186.

Giannetti, M. and Saidi, F. (2018). Shock propagation and banking structure. *Review of Financial Studies*, 32(7):2499–2540.

Greenwood, R., Landier, A., and Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, 115(3):471–485.

Guiso, L., Sapienza, P., and Zingales, L. (2013). The determinants of attitudes toward strategic default on mortgages. *Journal of Finance*, 68(4):1473–1515.

Gupta, A. (2016). Foreclosure contagion and the neighborhood spillover effects of mortgage defaults. *Journal of Finance*.

Gupta, D. (2019). Too much skin-in-the-game?: The effect of mortgage market concentration on credit and house prices. *The Effect of Mortgage Market Concentration on Credit and House Prices (January 28, 2019).*

Hart, O. and Moore, J. (1994). A theory of debt based on the inalienability of human capital. *Quarterly Journal of Economics*, 109(4):841–879.

Keys, B. J., Mukherjee, T., Seru, A., and Vig, V. (2010). Did securitization lead to lax screening? evidence from subprime loans. *Quarterly Journal of Economics*, 125(1):307–362.

Lorenzoni, G. (2008). Inefficient credit booms. *Review of Economic Studies*, 75(3):809–833.

Loutskina, E. and Strahan, P. E. (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *Journal of Finance*, 64(2):861–889.

Mayer, C. J. (1995). A model of negotiated sales applied to real estate auctions. *Journal of Urban Economics*, 38(1):1–22.

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *American Economic Review*, 100(5):1941–66.

Mian, A., Sufi, A., and Trebbi, F. (2015). Foreclosures, house prices, and the real economy. *Journal of Finance*, 70(6):2587–2634.

Milonas, K. (2017). The effect of foreclosure laws on securitization: Evidence from us states. *Journal of Financial Stability*, 33:1–22.

Morris, S. and Shin, H. S. (2004). Liquidity black holes. *Review of Finance*, 8(1):1–18.

Oehmke, M. (2014). Liquidating illiquid collateral. *Journal of Economic Theory*, 149:183–210.

Ortiz-Molina, H. and Phillips, G. M. (2014). Real asset illiquidity and the cost of capital. *Journal of Financial and Quantitative Analysis*, pages 1–32.

Pence, K. M. (2006). Foreclosing on opportunity: State laws and mortgage credit. *Review of Economics and Statistics*, 88(1):177–182.

Perotti, E. C. and Suarez, J. (2002). Last bank standing: What do I gain if you fail? *European Economic Review*, 46(9):1599–1622.

Petersen, M. A. and Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *Quarterly Journal of Economics*, 110(2):407–443.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? the information revolution in small business lending. *Journal of Finance*, 57(6):2533–2570.

Rajan, U., Seru, A., and Vig, V. (2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics*, 115(2):237–260.

Ramcharan, R. (2020). Banks' balance sheets and liquidation values: Evidence from real estate collateral. *Review of Financial Studies*, 33(2):504–535.

Scharfstein, D. and Sunderam, A. (2016). Market power in mortgage lending and the transmission of monetary policy. *Unpublished working paper. Harvard University*, 2.

Shleifer, A. and Vishny, R. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, 25(1):29–48.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, 47(4):1343–1366.

Stern, G. H. and Feldman, R. J. (2004). *Too big to fail: The hazards of bank bailouts.* Brookings Institution Press.

Wagner, W. (2011). Systemic liquidation risk and the diversity–diversification trade-off. *Journal of Finance*, 66(4):1141–1175.

Williamson, O. E. (1988). Corporate finance and corporate governance. *Journal of Finance*, 43(3):567–591.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data, mit press. *Cambridge, MA*, 108.

Tables

Table 1: Summary statistics

	Panel A: Main sample					
	Source	Mean	Std.Dev.	P5	P95	Observ.
$Approval_{i,n,0710}$	HMDA	.8618	.3451	0	1	3,876,615
$RetentionShare_{i,n,0406}$	HMDA	.0246	.0323	.0019	.0769	3,876,615
$HHI_{(i),n,0406}$	HMDA	.0129	.0133	.0049	.0291	3,876,615
$wDissim_{i,n,0406}$	HMDA	.0450	.0680	.00095	.1803	3,876,615
Loan Amount (000s)	HMDA	195.73	101.61	70	410	3,876,615
Minority	HMDA	.1526	.3596	0	1	3,876,615
Female	HMDA	.3127	.4636	0	1	3,876,615
Jumbo	HMDA	.0160	.1255	0	1	3,876,615
Loan-to-Income	HMDA	2.622	1.146	.929	4.600	3,876,615
LC_s	Fannie Mae	.6744	.2260	.4286	1	3,876,615
	Panel B: Further analysis					
	Source	Mean	Std.Dev.	P5	P95	Observ.
$Mergers_{i,0406}$	FRB Chicago & SoD	.0375	.1163	0	.2656	3,876,615
$Risky$ (Dummy $\geq LTI_{C,t}$)	HMDA	.5257	.4993	0	1	3,875,594
$NewHous_{n,0710}$	BPS	.0567	.1129	0	.259	1,012,211
$NewHous_{n,0710}$ (Dummy $\geq NH_{C,t}$)	BPS	.225	.417	0	1	1,012,211
Recourse dummy	Ghent and Kudlyak (2011)	.7734	.4186	0	1	3,876,615
$WeaknessQ_i$	CR & TFR	1.87	1.23	1	4	2,957,241
$Approval_{i,n,1114}$	HMDA	.8630	.3438	0	1	1,924,446
$Approval_{i,n,1417}$	HMDA	.8913	.3113	0	1	1,836,650
$RetentionShare_{i,n,1113}$	HMDA	.0314	.0451	.0030	.1048	1,836,650
$HHI_{(i),n,1113}$	HMDA	.0108	.0219	.0010	.0386	1,836,650
$wDissim_{i,n,1113}$	HMDA	.0391	.0660	.00030	.1644	1,836,650
$Origination_{i,n,0710}$	HMDA	.8513	.3557	0	1	3,602,856
$Highpriced_{i,n,0710}$ dummy	HMDA	.0657	.2440	0	1	3,067,126

Note: This table shows the source and summary statistics (average, standard deviation, 5th and 95th percentile, and number of observations) of the variables of the main application-level dataset. 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 the definition of the variables see table 6 in the Appendix.

Table 2: 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 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; $wDissimilarity_{i,n,0406}$, as the euclidean distance of retained-portfolio mortgages between a lender i and all other lenders in neighborhood n, and $HHI_{(i),n,0406}$ as the sum of squared retention share of all lenders in n, except for lender i's. 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 in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For the definition of the variables see table 6 in the Appendix.

Table 3: Instrumental variable estimation

	First stage		2SLS
Dep. variables:	RetShare	RetShare $\times LC_s$	Approval
	(1)	(2)	(3)
Mergers	-.0198***	-.0349***	
	(.0038)	(.00319)	
Mergers $\times LC_s$	.0847***	.0968***	
	(.00705)	(.00656)	
RetShare			2.614***
			(.400)
$\text{HHI}_{(i)}$			10.25***
			(1.719)
wDissimilarity			1.041***
			(.165)
RetShare $\times LC_s$			-3.084***
			(.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
R^2	.610	.634	.005
Kleibergen Wald F-stat			155.4

Note: The first six columns of table 3 show the first stage results of the 2SLS approach. Exploiting mergers among large ($\geq \$1billion$ in assets) banks, the instrumenting variable $Mergers_{i,z,0406}$ sum merged institutions' deposits as a fraction of total deposits within a zip code (source: Summary of Deposits); LC_s is the state s fixed liquidation cost index. The second stage (column 3) estimates the effect of fire sale risk 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 the definition of the variables see table 6 in the Appendix.

Table 4: 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	✓	✓	✓		✓	✓	✓
Neihgborhood FE	✓	✓	✓		✓	✓	✓
of Obs.	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

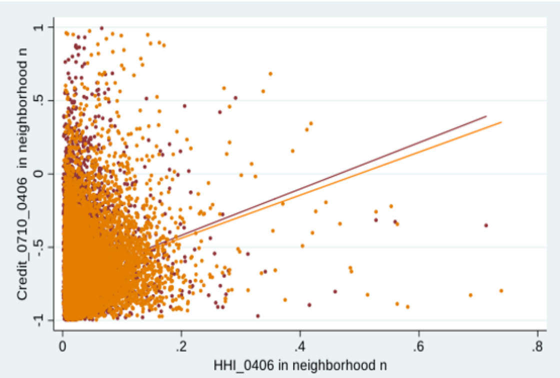
Note: Table 4 tests whether FSR proxies capture the *propping-up* theory instead. Model specification and all fire sale proxies remain the same as in the baseline model of equation (1), i.e. $RetShare_{i,n,0406}$, $wDissimilarity_{i,n,0406}$ and $HHI_{(i),n,0406}$. Panel A includes applications for house purchases in neighborhoods with new construction. This panel adds to the fire sale proxies an interaction term with the variable $NewHous_{n,t}$. 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, it takes value of 1 when the ratio is higher than the county-year average. Equivalently, panel B shows the specification, yet replacing $NewHous_{i,n}$ with the borrower Loan-to-Income (LTI). In column 5, LTI is the contionuos version of the 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 in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For the definition of the variables see table 6 in the Appendix.

Table 5: Further analysis

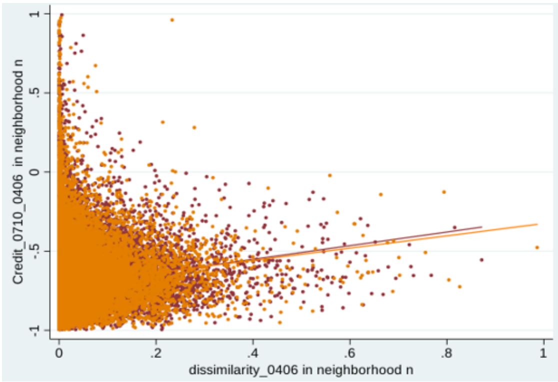
Dep. variable:	Approval					HPrice	Origination
Sub-sample:	Recourse	WeakL	RiskyB	2ndLien	2011-14	All	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RetShare	.850***	1.156***	.758***	1.390***	.505***	-.348***	.719***
	(.056)	(.072)	(.061)	(.161)	(.0684)	(.034)	(.048)
$\text{HHI}_{(i)}$	2.981***	5.70***	3.144***	1.877	2.305***	-1.329***	2.907***
	(.443)	(.690)	(.491)	(1.36)	(.473)	(.284)	(.397)
wDissimilarity	.381***	2.067***	.344***	.650	-.0722	-.151	.285***
	(.109)	(.776)	(.127)	(.598)	(.099)	(.095)	(.089)
RetShare $\times LC_s$	-.679***	-1.013***	-.525***	-1.008***	-.229***	.264***	-.419***
	(.068)	(.088)	(.079)	(.232)	(.087)	(.040)	(.063)
$\text{HHI}_{(i)} \times LC_s$	-2.843***	-5.810***	-2.940***	.732	-2.017***	1.111***	-2.463***
	(.545)	(.875)	(.613)	(2.082)	(.570)	(.320)	(.509)
wDissim $\times LC_s$	-.399***	-2.335*	-.307*	-.766	.202	.00859	-.232*
	(.149)	(1.28)	(.184)	(1.07)	(.141)	(.134)	(.126)
Borrowers' controls	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Neighborhood FE	✓	✓	✓	✓	✓	✓	✓
# of Observations	2,997,351	1,805,874	2,036,022	230,060	1,922,631	3,065,783	3,601,794
R^2	.125	.098	.144	.267	.113	.226	.133

Note: This table presents application-level OLS estimates keeping the same structure of the baseline model (table 2, column 6), yet focusing on different sub-samples (columns 1-6) or different dependent variables (7-8). In column 1, we run the model 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 distribution); column 3 explores the fire sale risk effects on risky borrowers, defined as applicants with an LTI larger than the county-year average; column 4 subsets second-lien and no-lien applications. In column 5 we study lenders' approval decision on applications arriving in 2011-2014, conditioning on fire sale risk proxies in 2004-2006; The dependent variable in column 6 is $HPrice_{i,n,0710}$ that takes the value of one if the interest rate charged on accepted loans is higher than the Treasury rate. Last column replaces the previous dependent variable with the dummy $Orig_{i,n,0710}$, taking value of one if the mortgage application is accepted by the lender and the contract is accepted by the borrower; zero otherwise. Zip code-clustered standard errors in parentheses. *, **, *** represent p-values below 0.05, 0.01 and 0.001, respectively. For the definition of the variables see table 6 in the Appendix.

Figures



(a) Concentration and Credit Volume Changes



(b) Portfolio Dissimilarity and Credit Volume Changes

Figure 1: Macro Evidence. Relationship between change in Credit Volumes, on the y-axis, and Fire Sale Risk, on the x-axis. The concentration (Herfindahl-Hirschman) Index HHI (figure 1a) is calculated at neighborhood n level first, and aggregated at state level using the relative credit volume in n. Portfolio orthogonality (figure 1b) is at lender i-neighborhood n level and it is first aggregated at the neighborhood n using the local retention share of the lender, and only then using the relative credit volume in n as a weight for the state level value. Orange (Red) dots and line refer to states with foreclosure costs above (below) all states average value.

Appendix

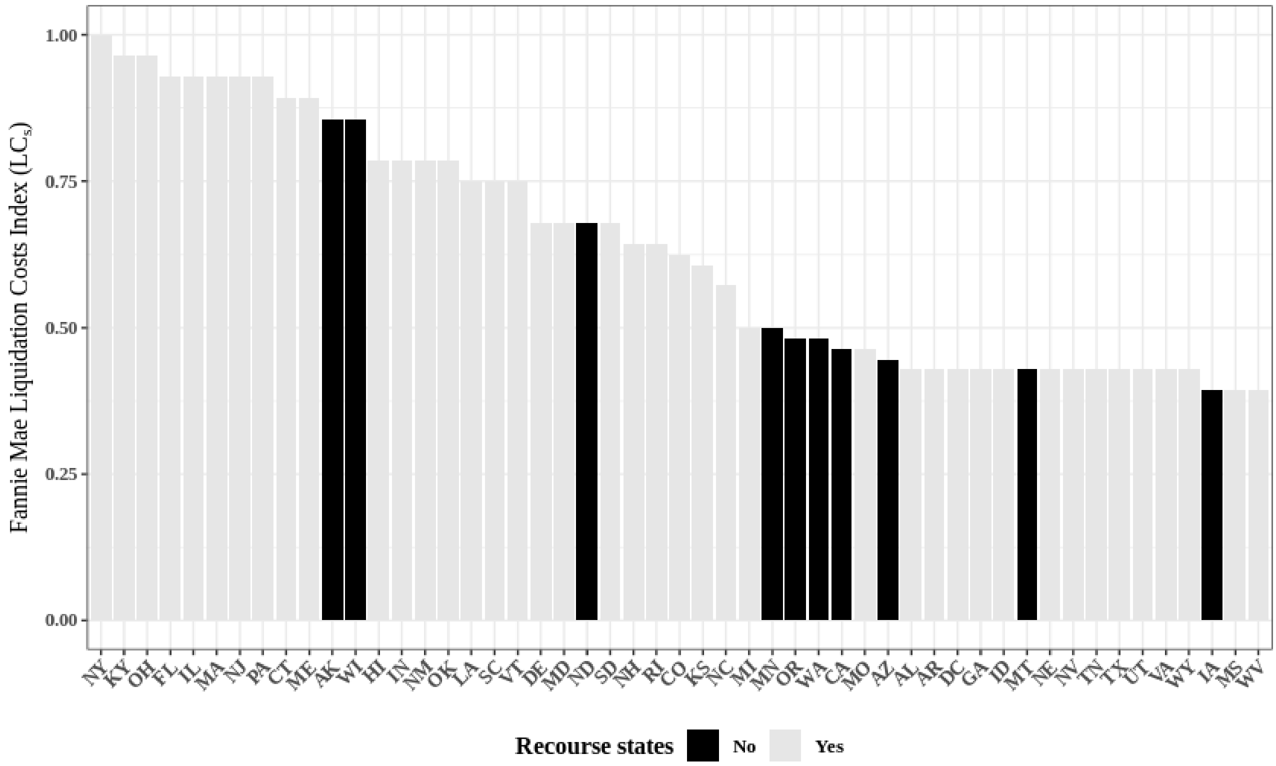


Figure 2: Fannie Mae US Foreclosure Costs Index. This figure plots the foreclosure attorney's and Trustee's fees per state - scaled down by the most expensive one - that we use in our regressions. Black (white) bars indicate states without (with) recourse clause.

Table 6: Variables Definition

Variable	Definition	Variable	Definition
$Approval_{i,n,0710}$	Dummy variable, taking 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 value of one if a mortgage application is originated, that is accepted by both the lender and the borrower; zero if the either party rejects it;	$Risky$	Dummy variable, taking value of one if a borrower's LTI ratio is equal or above the county's average LTI; zero otherwise;
$HighPriced_{i,n,0710}$	Dummy variable, taking 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 construction home 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 in the balance sheet as a fraction of total mortgages originated, over 2004-2006 in census tract n;	$HighNewHous_{n,0710}$	Dummy variable, taking 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 each other lender ($\neq i$) 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, per 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 value of one if the borrower applicant is reported in HMDA data as Asian, Hispanic or Black; zero otherwise;
$Female$	Dummy variable, taking 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 value of one if the mortgage application is a jumbo loan, zero otherwise;	$Recourse_s$	Dummy variable, taking value of one if the house serving as collateral for the mortgage application is in a state s requiring Recourse clause; zero if state s does not allow for the Recourse clause;

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

Table 7: 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.