Small bank lending in the era of fintech and shadow banking: a sideshow?*

Taylor A. Begley†
Kandarp Srinivasan‡

September 18, 2019

Abstract

Mortgage lending by the four largest banks (Big4) dropped from 30% to 23% of the market from 2009-2013 following crisis-related fines and heightened regulatory burden. Aggregate patterns suggest this gap was filled by nonbank lenders (26% to 37%). However, amidst these secular *aggregate* trends, we present new county-level facts showing that small banks were twice as responsive as shadow banks to fill the *local* gap left by the Big4 retreat, and more than four-times more responsive than fintech lenders. We find that cross-sectional variation in consumer preferences for traditional banks and institutional features of the mortgage market play important roles in explaining our findings. Our results highlight the continued importance of small banks despite the rise of shadow banks and financial technology disruption.

Keywords: small banks, shadow banks, fintech, mortgage market, mortgage lending.
JEL Classification: G2, L5

*First Draft: November 18, 2018. We are grateful to Radha Gopalan, Todd Gormley, Peter Haslag, Mark Leary, Asaf Manela, Amiyatosh Purnanandam, Anjan Thakor, Daniel Weagley, and seminar participants at the Boston Fed, George Mason, Northeastern, and Washington University in St. Louis for helpful comments on the paper.

†Olin Business School, Washington University in St. Louis; email: tbegley@wustl.edu.
‡D'Amore-McKim School of Business, Northeastern University; email: kandarp@northeastern.edu.

1 Introduction

The composition of mortgage credit supply has undergone major changes since the financial crisis. Increasing regulatory burden (Dodd-Frank, stress tests, mortgage lawsuits) has hit the largest banks hard, and their market share has fallen from 30% in 2009 to 23% in 2013. Meanwhile, nonbanks have seen staggering gains in aggregate shares from 26% to 37%. These stark patterns have led many to speculate on the future of traditional banks and, in particular, on the relevance of small, local banks as suppliers of mortgage credit. Indeed, both heightened bank regulation and rapid technological change (Buchak, Matvos, Piskorski, and Seru, 2018a; Fuster, Plosser, Schnabl, and Vickery, 2019) are ostensibly bad news for the small banks. If that is the case, the diminishing role of traditional local lenders is a cause for concern because changing market composition has substantial consequences for housing rents, wealth inequality, and systemic risk.[1] Are small banks still relevant for mortgage lending despite new regulatory and technological headwinds? In this paper, we uncover compelling new facts about the enduring importance of small banks in local markets and examine channels through which they persevere.

The ongoing relevance of small banks in mortgage lending is unclear. In a market with limited nonbank presence (small business lending), Cortés, Demyanyk, Li, Loutskina, and Strahan (2018) show that where the large banks retreat because of stress testing and relatively higher regulatory costs, small banks increase their activity. In mortgage lending, however, small banks face competition from nonbank lenders, and these lenders face relatively lower regulatory costs. If anything, nonbanks may be *better* positioned to fill the gap left by the larger banks (Buchak et al., 2018a). This distinct source of competition is especially consequential because nonbanks play a major role in the mortgage market (more than one

[1] D'Acunto and Rossi (2017) show that the areas with lower share of big banks experience a redistribution of credit supply away from smaller loans toward larger (jumbo) loans, and Gete and Reher (2018) show that the retreats leads to higher housing rents and mortgage denial rates. Kim, Laufer, Stanton, Wallace, and Pence (2018) raise concerns about systemic risk because of the inherent vulnerability of nonbanks to liquidity pressures.

third by the end of our sample). Further, technology plays a critical role in much of mortgage lending today (Fuster et al., 2019) with Quicken Loans, for example, establishing itself as a top mortgage lender.[2] Given their lack of technological firepower, local banks are at a substantial competitive disadvantage to fintech lenders on this dimension.

On the other hand, a large body of banking research suggests traditional banks (small banks in particular) have a relative advantage in lending that requires soft information or balance sheet retention (e.g., Boot and Thakor, 2000; Berger, Miller, Petersen, Rajan, and Stein, 2005; Berger, Bouwman, and Kim, 2017). Thus, nonbanks, who have very little scope for making loans that cannot be securitized, are at a stark disadvantage for these types of loans (Buchak, Matvos, Piskorski, and Seru, 2018b). Further, because of prior relationships or reputation, some borrowers may have a preference for transacting with a bank rather than nonbank for reasons of familiarity, comfort, or trust (e.g., see Merton and Thakor, 2018), or because of the bundling of services that banks can provide.

We explore these economic channels by studying county heterogeneity in the response of small banks (those with assets less than $10 billion) and nonbanks – which includes both traditional "shadow bank" lenders such as independent mortgage companies as well as fintech lenders – to the post-crisis retreat by the "Big4" banks (Bank of America, Citi, JP Morgan, and Wells Fargo). Our focus on withdrawal by the largest four banks is motivated by Gabaix (2011) who argues decisions by a few large firms can have a sizable aggregate impact on the industry. We show small banks provide a countervailing source of mortgage credit against the withdrawal of the Big4, that is locally *stronger* than that of the non-banks. In contrast, the strong growth in nonbank lending has been more uniform across the country, but less sensitive to *local* (county) variation in the Big4 retreat. We are the first to uncover this nuanced picture of the post-crisis transformation in mortgage lending. We also provide evidence that consumer preferences for borrowing from a bank (over nonbanks) and supply-side institutional frictions (balance sheet capacity) play important roles in explaining our findings, and that

[2] https://www.quickenloans.com/press-room/fast-facts/

small banks can partially mitigate the adverse redistributive effects of big bank withdrawal shown in D'Acunto and Rossi (2017).

During the immediate post-crisis period of increasing regulation and crisis-related fines (2009-2013), there was a sharp withdrawal of the Big4 (30% share to 23%–over half a million loans).[3] We focus our study on the responses across three different *lender-classes*: small banks (assets less than $10 billion), shadow banks (non-depository institutions, excluding fintech, such as independent mortgage companies), and fintech lenders.[4] Clear aggregate patterns emerge alongside the significant retreat of the Big4: shadow banks (24% to 30%) and fintech (2% to 7%) have large gains. These facts are consistent with the popular narrative that there is a pure transfer in market share from traditional banks to nonbanks. Our analysis, however, begins with two striking facts: First, despite the increases in regulation, compliance costs, and technological disruption from competitors, the small bank share of the market is virtually unmoved, remaining around 17% of the market throughout the sample period. Second, while the aggregate share of small banks is at 17%, their *local (county)* response to changes in Big4 share is the strongest among lender classes.

A key message in our paper is that the evolution of the aggregate composition of lenders masks significant heterogeneity at the local, county-level. In our baseline tests, we regress the 2009-2013 change in county share of mortgage originations on the change in county share of Big4 originations. A one-standard-deviation larger decrease in county-level Big4 share (about 8 percentage points) corresponds to an increase in small bank share of 4.7pps.[5] After accounting for the aggregate trends in share changes (i.e., the secular increase in nonbank

[3]The Big4 faced over $150 billion in fines, global systemically important bank (G-SIB) designation (which entailed heightened oversight and stringent capital and liquidity requirements), changes to mortgage servicing rights treatment, stress testing, heightened concerns and uncertainty about GSE "put-backs" of loans that perform poorly ex post, and uncertainty surrounding the use of the False Claims Act (e.g., see Stein et al., 2014; Lux and Greene, 2015; McCoy and Wachter, 2017). While we focus on the 2009-2013 period for cleaner identification, our results are robust to adjusting these start and end dates.

[4]For completeness, our baseline results on market share changes include "large" banks (those with assets greater than $10Bn, but smaller than the Big4) and credit unions.

[5]In 2009, the *county-level* averages shares were as follows: Big4 (22.5%), large banks (18.9%), small banks (33.6%), credit unions (6.1%), shadow banks (16.7%), and fintech lenders (2.3%).

mortgage lending), small banks pick up more than half of the loans to longer made by the Big4. Growth in origination shares for shadow banks and fintech lenders is much less sensitive: a one-s.d. larger drop in Big4 share is associated with a 1.7pps and 0.2pps increase, respectively.

While our baseline tests focus on the changes in lending *shares*, we also examine changes in the absolute *level* of county lending (i.e., raw loan growth) of each lender class. Consistent with our "shares" results, small banks were indeed most responsive by also expanding their lending *volume* in areas vacated by the Big4 and were not just mechanically increasing their share as a result of changes in market size. In areas with a one-s.d. lower Big4 growth rate, small bank mortgage lending grew more than three times faster than shadow banks and nearly eight times faster than fintech lenders.

The interpretation of our baseline estimates may be clouded by omitted county-level factors that correlate both with local Big4 lending declines and increases in lending by the other lender classes (small banks in particular). For example, growth prospects may differentially affect the relative attractiveness of that market across lender classes. Another concern might be that the small banks were the prime movers in this market and they pushed the Big4 out of their respective counties (i.e., reverse causation). We address these concerns below.

We first note that our regressions involve within-county changes which differences out time-invariant unobservables, so any concerns must relate to an omitted *time-varying* unobservable that correlates both with Big4 withdrawal and increase in small bank share, but not so much for shadow banks or fintech lenders. We control for county demographics (overall population, minority population, income, subprime share) and the structure of the local lending market (bank HHI, number of bank and nonbank lenders), which are likely factors related to, for example, unobserved changing growth prospects.[6] Next, we use the 2009 mortgage origination

[6] We also find that areas of greatest Big4 retreat do not have, on average, lower populations, lower income, or lower credit scores, so an explanation based on declining growth prospects seems unlikely in our setting.

share of the Big4 as an instrument for the ensuing 2009-2013 changes in Big4 shares. In 2009, the majority of crisis-related fines had yet to be levied, and the increases in the regulatory burden of the Dodd-Frank Act had not yet passed. Our use of a predetermined measure of the distribution of Big4 shares is in the same spirit as the IV strategies in D'Acunto and Rossi (2017) and Gete and Reher (2018). Unlike this line of work, we instrument for *changes* in Big4 share, not the levels. The relevance of our instrument hinges on the fact that the scope to reduce mortgage lending is highest in counties where lenders have a larger initial mortgage share. The 2009 Big4 share is a strong predictor of 2009-2013 share decline (i.e., strong first stage). The IV estimates of the response of small banks to a one-s.d. larger decline in Big4 is 5pps - similar to the OLS estimate. The effects for shadow banks and fintech each are considerably smaller at about 1pp.

Our IV exploits geographic variation in initial conditions – larger declines are (mechanically) more likely to occur in areas with larger initial shares. The exclusion restriction states that the Big4 2009 *level* of county share of mortgage originations is related to the 2009-2013 *change* in small-bank county share of originations only through its effect on the 2009-2013 change in Big4 share. While we can never (formally) test for the exclusion restriction, we confront the concern that time-varying, county-specific factors could possibly violate it, by disaggregating data to the *lender-county* level. This allows us to use our IV strategy to compare growth rates across lender classes while simultaneously accounting for both county fixed effects and lender fixed effects. We exploit variation in exposure to the Big4 within a lender's geographical footprint, while holding county and lender characteristics fixed.[7] Specifically, we regress the 2009-2013 lender-county loan growth on lender fixed effects, county fixed effects, and the interaction of lender class and change in county-level Big4 share. By adding county fixed effects in a regression of *differences*, we can rule out explanations related

In additional tests, we use propensity score and mahalanobis matching to ensure comparability of counties with different exposures to the Big4.

[7]Using an IV with county fixed effects help address the reverse causation argument that county-specific attributes (correlated with 2009 Big4 shares) led small banks to increase shares from 2009 to 2013 and out-compete the Big4 from these areas.

to time-varying factors such as average changes in local demand, house prices changes, or changes in economic prospects from 2009-2013. Lender fixed effects rule out lender-specific issues including unobservable shocks to a bank's capital or differences in regulatory burden and scrutiny. This within-lender test shows a substantial reallocation of lending toward areas where the Big4 have retreated, with the strongest response from small banks.

Why are small banks so responsive to changes in the lending of the Big4? We focus on county characteristics that correspond with particular credit demand or supply factors. On the demand side, some borrowers may prefer to deal with brick-and-mortar institutions if feelings of perceived trust and reliability play a role in if borrowers' decision making. We tackle the challenge of quantifying borrower propensity by introducing a new measure of a county's average long-term consumer preference for borrowing from banks (as compared to nonbanks).[8] We find that counties with a larger relative preference for banks over nonbanks have higher growth in small-bank lending share in response to the Big4 retreat compared to the other lender classes.

On the supply-side, differences in balance sheet capacity directly affects the willingness and ability to engage in origination activity (Buchak et al., 2018b), especially for loans that are hard to re-sell into the securitization market. Thus, in areas with greater balance-sheet financing needs, small banks would be a natural substitute for the Big4 relative to nonbanks, since the latter offer virtually zero on-balance-sheet financing. We consider counties with relatively fewer loans going to government-supported loan programs (GSLPs) such as those related to Fannie Mae, Freddie Mac, or FHA programs. We find that small banks increased share most in counties which have historically had lower shares of GSLP loans (i.e., higher need for on-balance-sheet financing). In sum, we conclude that the striking increase in share for small banks in areas where the Big4 withdrew is driven both by consumer preferences for

[8]We separately measure the preference for banks and then nonbanks by computing the share of loans *approved* by that lender group that ends up *accepted* by borrowers (i.e., group-specific loan conversion rates) in the years leading up to the sample period. The difference in the county's bank and nonbank conversion rates is our measure of relative preference for banks.

dealing with a bank on the credit demand side as well as structural features of the supply side of credit.

Finally, we consider a case study of Bank of America to strengthen the causal interpretation of our results and relate them to Gabaix's (2011) "granular" hypothesis: when the empirical distribution of lenders is "fat-tailed" (i.e. a few, very large players at the top), individual decisions can have substantial aggregate effects on the industry. We examine the Gabaix (2011) argument at its limit using the withdrawal of a *single* large lender and tracing out the effects on the behavior of others in the market. We show BoA's withdrawal had significant changes in the composition of mortgage supply, with small banks being most responsive to BoA's retreat. We also bolster these results by introducing another instrument for BoA's 2009-2013 retreat in addition to the 2009 BoA share: Countrywide's 2007 origination share (i.e., before being acquired by BoA). In the years after the $2.5 billion acquisition, there began an avalanche of unanticipated legal troubles and fines from Countrywide's pre-crisis activities, which have been more than $50 billion. After using the Countrywide acquisition to bolster their share, BoA became soured to the mortgage business and began pulling out of the market. Using 2007 market shares addresses concerns of time-varying unobservables related to the financial crisis period as well as any possible anticipatory effects of Dodd-Frank Act. Using this IV, we find that a one-s.d. larger decrease in county-level BoA share corresponds to about 3.2pps increase in small bank share. The estimates for shadow banks and fintech are about 1pp and less than 0.5pps, respectively, using either instrument.

2 Related Literature

Our paper is related to recent work on changes in the U.S. mortgage market including Buchak et al. (2018a), Buchak et al. (2018b) and Fuster et al. (2019). These papers study the rise of "shadow banks," a term broadly referring to nonbank lenders, including fintech and non-fintech companies.[9] Buchak et al. (2018a) assess the relative contributions of regulation and technology in disrupting the mortgage market. While traditional banks collectively move out of residential lending upon facing greater regulatory scrutiny (and capital costs), shadow banks take advantage of this regulatory arbitrage. The authors attribute 60% of shadow bank growth to the increased regulatory burden on traditional banks and 30% to technological advantages. Fuster et al. (2019) particularly focus on the role of technology in the rapid rise of fintech lenders in the mortgage market. They conclude that technology has improved efficiency in the mortgage market and argue this alleviates capacity constraints associated with traditional mortgage lending. Our work also documents the increasing aggregate shares of shadow banks and fintech lenders, but we highlight that their market penetration and growth are more even and widespread. We highlight that local changes in nonbank lending is much less sensitive to the Big4 banks' retreat than small traditional banks. We also present new facts that show that the broad retreat of traditional banks is concentrated in the larger banks while small banks actually maintain their aggregate share.

Buchak et al. (2018b) study limits to the expansion of shadow banks in jumbo lending markets because the vast majority of these "non-conforming" loans are retained on balance sheets, which provides a comparative advantage for traditional banks. We differ from existing work by documenting new facts about the heterogeneity *within* the broad category of traditional banks across banks of different sizes. We build on Buchak et al. (2018b) by showing that areas with a higher need for balance sheet financing are the areas where small banks are relatively better suited (compared to nonbanks) to fill the lending gap left by the Big4.

Small and large banks often vary on several dimensions including their access to funding, screening criteria, and regulatory burden. While sometimes viewed as less sophisticated and further from the technological forefront, small banks have been critical for issues such as

[9] Other work focusing on the role of regulatory arbitrage in the shadow banking sector during the lead-up to the crisis include Gorton, Metrick, Shleifer, and Tarullo (2010), Adrian and Ashcraft (2012), and Acharya, Schnabl, and Suarez (2013)

relationship lending (Petersen and Rajan, 1994; Hein, Koch, MacDonald, et al., 2005; Bolton, Freixas, Gambacorta, and Mistrulli, 2016) and local knowledge of the borrowers (Berger et al., 2005; Loutskina and Strahan, 2011; Gilje, 2017). Our work highlights the continuing importance of small banks, even in a market characterized by rapid technological change and increases in competition from nonbanks (Boot and Thakor, 2000).

A growing body of evidence investigates whether post-crisis Big4 retreat had real effects. D'Acunto and Rossi (2017) provide evidence that regulation perturbed the credit supply decisions of the top twenty banks, leading them to shift to making large (jumbo) loans at the expense of making smaller loans, thus disrupting the supply of credit and contributing to increases in wealth inequality. Gete and Reher (2018) show that the impact of the retreat of Big4 results in greater housing rents due to the overall contraction in mortgage supply. Gete and Reher (2018) argue frictions prevent the costless substitution across lenders, ultimately leading to greater difficulty in the access to credit. In the spirit of this argument, we show a persistent borrower preference for dealing with depository institutions could explain why small banks are relatively more sensitive to Big4 presence than are shadow banks. Chen, Hanson, and Stein (2017) study the decline of small business credit provided by large banks during the post-crisis period. Counties where big banks had the largest market share pre-crisis experienced a rise in interest rates, fall in small business credit, and a drop in wages from 2006 to 2010. Cortés et al. (2018) show that stress-tested banks reduce their small business credit supply, and small banks increase their small business credit supply these areas. Our setting is in a fundamentally different credit market in terms of the product (mortgage vs. small business loans) and the competitive environment. Unlike small business lending, over a third of the loans are originated in the market are made by nonbanks by the end of our sample. Our results show how small banks respond most sharply to help fill the gap left in mortgage credit when the larger banks withdraw, even in the face of this increasing presence of nonbanks.

Finally, our work relates to Gabaix (2011), who shows that the actions of a single large player in an industry (e.g., Bank of America) can have large ripple effects throughout the market. While much of the literature on large bank behavior has focused on too-big-to-fail (TBTF) in terms of issues such as systemic risk and potentially inefficient risk taking, we show that the behavior of TBTF banks can have far-reaching implications even in normal times.

3 Data and Summary Statistics

Mortgage originations data are from the Loan Application Register (LAR) files of the Home Mortgage Disclosure Act (HMDA) database. In our analysis, we include all originated loans whose purpose was either home purchase or refinancing. For our analysis, we measure lending activity as the number of loans, although we could similarly do the analysis using loan amounts. We classify HMDA lenders into banks and nonbanks. Nonbanks are non-depository institutions that participate in mortgage credit origination. We subdivide nonbanks into those that specialize in using financial technology (*fintech lenders*) and those that do not (*shadow bank lenders*). We classify lenders as fintech those with a strong online presence with nearly all of the application process occurring online and without human interaction (specifically, we follow Buchak et al., 2018a). HMDA lenders ("respondents") only report direct parent affiliations instead of the ultimate holding company (Avery, Brevoort, and Canner, 2007). We use the HMDA Lender file from Robert Avery to associate depository institutions and mortgage companies with their ultimate parents. This avoids a fundamental problem of misclassifying subsidiaries – affiliated mortgage companies are folded into the holding organization and then reported on an aggregated basis in our sample. We then aggregate the data to the lender-county level.

Where applicable, the Avery file also includes the RSSD ID for the lender, which allows us to the match the bank HMDA lenders to their call report (bank-level) and deposit data (bank-county level). Since much of our analysis involves making comparison across different lender classes based on size, we classify each bank according to their size in 2011. Each lender is classified into one of the following six groups: Big4 (Bank of America, Citi, JP Morgan, Wells Fargo), large banks (2011 assets between $10 billion and $1 trillion), small banks (2011 assets less than $10 billion), credit unions, shadow banks, and fintech lenders.

Our final dataset is a lender-county panel containing those lenders present from 2009-2013. Some tests include controls for county-level demographic or house price data, which we collect from the Census and FHFA respectively. Table 1 presents the 2009 county-level summary statistics for these variables in Panel A. Panel B presents the average initial conditions of the counties in 2009 with respect to shares of originated mortgage loans.

4 Big4 Retreat and Changing Lender Composition

We first examine trends in mortgage origination activity during the sample period for each of six groups of lenders: Big4 (Bank of America, Citi, JP Morgan, Wells Fargo), banks with asset size between $10 billion and $1 trillion ("large banks"), banks with asset size less than $10 billion ("small banks"), credit unions, shadow banks, and fintech lenders. Figure 1 presents a line chart of the share of lending (both purchase and refinancing loans) for each group, with the bar chart showing the aggregate lending activity for the sample.

For our sample, the *aggregate* share of new loans issued by the Big4 banks drops during 2009-2013 from 30% to 23%, while there is also a drop in share for large banks from 19% to 15%. There were stark increases in the shares of nonbanks: shadow banks (24%-30%) and fintech lenders (2%-7%). Despite the surge in shadow bank and fintech activity, the share for small banks has remained strikingly stable remaining around 17%-18%. This new fact about heterogeneity within bank lenders was masked in prior work which, primarily considers the bank versus nonbank margin. Next, we move to county level analyses to examine whether patterns of the Big4 and nonbanks in Figure 1 are driven by a pure transfer between these groups.

Given the widespread retreat of the Big4, how might various lender classes (small banks, fintech, etc.) respond to these changes at the local, county level? A leading hypothesis is that county-level patterns should mirror the aggregate changes shown in Figure 1: shadow banks and fintech fill the void left by the Big4, while other lender classes are unresponsive to the Big4 retreat. A second hypothesis is that variation in lender-class behavior is driven by a marginal increase in the regulatory burden on all banks. Specifically, this predicts that nonbanks (shadow banks and fintech lenders) will be most sensitive to Big4 withdrawal (i.e., negatively correlated with Big4), while small banks and (non-Big4) large banks will retreat alongside the Big4 as they face increased regulation on the margin (Buchak et al., 2018a). A third hypothesis is that fintech lenders, with a lower marginal cost of entry and superior technology (Fuster et al., 2019), will respond the strongest to the Big4 retreat. Finally, if traditional bank lending remains important for this market, small banks may capture the customers left by the Big4.

4.1 Local Response to Big4 Retreat: Quintile Averages

We now focus our analysis on the local, county level where we examine the change in the county share of mortgages from 2009-2013. For our baseline tests, we aggregate the data (e.g., the number of loans originated) to the county level for each of the lender classes.

Table 2 shows that the overall *average* county-level results mirror the aggregate results shown earlier (Figure 1), with net withdrawals from the Big4 (-5.8pps) and other large banks (-3.8pps), net increases for shadow banks (+5.3pps) and fintech (+3.8pps), and relative stability for small banks (-1.0pps) and credit unions (+1.6pps).[10] The results also show that these average changes for the groups mask substantial variation across quintiles, particularly for small banks. Small banks' change in shares of origination has a large negative relationship

[10]Note that these are county-level averages and thus differ from the aggregate statistics simply because of variation in the number of mortgages across counties.

with Big4 changes: small banks share increased by 5.9pps in the quintile of counties where the Big4 had their largest withdrawal, while it decreased 6.7pps in the quintile of counties where the Big4 most increased their share. While the other classes of lenders also exhibit a negative relationship, the economic magnitude of the relationship between the Big4 and small banks dwarfs the others. Figure 2 shows the results graphically with the bar representing the average Big4 withdrawal for the quintile and the lines representing the associated changes in county-share of originations for the other lender classes.

Table 3 show how the quintiles differ on other dimensions. The Big4 retreat was strongest in areas with slightly higher per capita income and lower subprime populations. However, population, racial diversity, and bank competition are not monotonically related to Big4 withdrawal. Appendix Table A.1 shows differences in county characteristics according to the *level* of the 2009 Big4 county share. In 2009, the Big4 typically had larger shares in areas with higher populations, higher minority shares of population, higher incomes, lower subprime shares, and more bank competition. We control for these observable characteristics in all of our regressions.

4.2 Local Response to Big4 Retreat: Regression Estimates

We now examine these relationships in a regression context by estimating the following county-level, 2009-2013 differences model separately for each lender class:

$$\Delta Share_{county}^{LenderClass} = \phi\left(\Delta Share_{county}^{Big4}\right) + \zeta_{stateFE} + \Gamma X_{county} + \epsilon_{county} \tag{1}$$

The regression of changes in share will difference out time-invariant factors that might affect changes in lender composition such as baseline demand conditions and profitability. We also include state fixed effects to control for any state-level differences in trends such as legal environment and growth rates in shares for different lender classes and X_{county} controls for county demographic or local market characteristics. We also cluster standard errors at the

MSA level to account for local spatial correlations that go beyond the county level. To ease interpretation, we standardize the independent variables to zero mean and unit standard deviation. Given that the regressions focus on shares, it must be the case that when the Big4 decrease their share, the sum of the remaining constituent shares must increase (we examine raw growth later). What we wish to examine is heterogeneity in response: whether this response is uniform across lender classes, is dominated by the shadow banks and fintech lenders that were gaining aggregate market share over this time period, or something different. Table 4 presents the results with each column representing a different lender class.

Column (1) indicates small banks are highly sensitive to the changes in origination share of the Big4. A one-s.d. decrease in Big4 share (about 8pps) corresponds to a 4.7pps increase in the origination share of small banks during the time period. At the bottom of the table, we also include the mean of the dependent variable for reference which shows that there was an average decline of 1pps across all counties. There is also an effect for shadow banks and fintech lenders (columns 2 and 3), although it is substantially smaller at 1.7pps and 0.2pps share increase, respectively. Thus, while those classes of lenders experienced a secular increase in average county share (5.3pps and 3.7pps), the growth in lending share was much less sensitive to variation in Big4 withdrawal. After accounting for the aggregate trends in share changes, the estimates in Table 4 indicate that small banks pick up over half of the loans no longer made by the Big4. Column (4) shows that the change in origination share of large banks ($10bn-$1tr) is not sensitive to the changes of the Big4. Large banks are likely closer to the Big4 in terms of their regulatory burden and business model, so an overall decline in their lending shares is unsurprising. Column (5) shows that Credit Unions do have sensitivity to the Big4, but it is economically small. Given the institutional features that limit credit union lending (e.g., borrowers belonging to a particular profession), these results are also not particularly surprising. For the remainder of the paper, we will focus on small banks, shadow banks, and fintech lender but will present the results for all lenders for completeness.

As an alternative way of presenting the results, we combine each lender-class × county-share observation (except Big4 share) in a single regression with indicator variables for each lender class and their interaction with the change in Big4 share. We estimate these regressions including an indicator for each class and leave out the intercept allowing direct interpretation of the indicator variable coefficients as the average county-level change in origination share. Specifically, we estimate the following for each county c and lender class LC.

$$\Delta Share_{c,LC} = \Lambda \mathbb{I}_{LC} + \Psi \left(\mathbb{I}_{LC} \times \Delta Share_c^{Big4} \right) + \zeta_{stateFE} + \Gamma X_c + \epsilon_{c,LC} \tag{2}$$

$\hat{\Lambda}$ is a vector of estimated average change for each lender class during the sample, while the variable of interest is $\hat{\Psi}$, which corresponds to the lender-class-specific sensitivity to county-level Big4 retreat. Table 5 presents the results, with columns (1-2) mirroring the results in Table 4. For column (3), we standardize the dependent variable (change in lender-class share) to have mean zero and unit standard deviation within each lender class. This normalization makes the lender-class indicator variables redundant and allows us to directly compare the economic magnitudes of the response for each class. The coefficient on small banks of -0.420 indicates that a one-s.d. larger drop in Big4 share corresponds to a 0.420-s.d. (i.e., standard deviation across counties for small banks). This normalization accounts for the differing initial shares across class (e.g., small banks and shadow banks have substantially larger shares than fintech) and shows that the relative response of small banks is more than twice that of shadow banks and four-times larger than that of fintech. While shadow banks and fintech are making secular gains in the aggregate lending share, small banks are most responsive at the county level to fill the gap in market share left by the Big4 retreat. These results do not support the idea that the aggregate changes in the mortgage market are mirrored at the local level, but rather provide strong support to the hypothesis that small banks are providing a substantial countervailing source of credit where the Big4 are withdrawing.

To further ensure comparability on observables across counties with differing levels of

Big4 retreat, we also estimate the respective lender-class responses using matching. As the treatment variable, we simply divide the counties into above-median (treatment) and below-median Big4 retreat. We match the treatment counties to three nearest matched neighbors based on observable 2009 county characteristics. We use both propensity score matching and mahalanobis distance matching, and we find similar results to our baseline tests above. Appendix Table A.2 presents the results, and Appendix Figure A.1 presents some matching diagnostics that demonstrate the comparability of treatment and control firms.

4.3 Local Response to Big4 Retreat: IV Estimates

In the analysis above, there may be a concern about the decisions of where and to-what-extent the Big4 banks withdrew following the crisis and its accompanying regulatory fines and penalties. Specifically, there may be concerns about unobserved time-varying county factors that drive Big4 withdrawal and small bank growth. To cast doubt on our results, it must be true this factor not only relates to Big4 retreat and small bank advance but also has relatively smaller relationship with changes in shadow bank or fintech lending.

For example, consider if a county-level decline in economic prospects (that is not captured by our local demographic and lending market controls) causes Big4 banks to withdraw. If declining prospects also cause small banks, but not shadow banks or fintech lenders, grow in these areas, then our earlier results may be confounded. Note that the raw correlation between Big4 withdrawal and characteristics related to economic prospects do not seem to suggest this story to be likely (as shown earlier in Table 3). In any case, we address this concern using an instrument for the Big4 withdrawal.

We use the Big4 lending share in 2009 (prior to the sharp increase in regulatory burden) as a county-level instrument for Big4 withdrawal. The instrument does not condition on the actual withdrawal, but rather it simply identifies counties where Big4 had the largest presence and thus a larger scope for withdrawal. Before their post-crisis retreat from mortgage lending, there was a great deal of variation in Big4 origination share across the country. In 2009, the Big4 accounted for about 23% of new loans in the average county, with a range of 9%-39% share from the 10th to 90th percentile. Because of this geographical variation in initial conditions, there is substantial variation in the size of the gap left when the withdrawal began. For the average county, the Big4 share dropped about 6pps with a 10th-90th percentile range of 16pps decrease to 2pps increase. Naturally, the counties where the Big4 had the largest presence are the counties where there is the greatest scope for meaningful withdrawal. Figure 3 shows a scatter plot and fitted line of this strong "first stage" relationship. A 10pps higher 2009 Big4 share in a county is associated with an economically and statistically significant drop of 4.6pps in share from 2009-2013.

Figure 4 shows the geographical variation in Big4 share in terms of their initial 2009 dispersion (panel 4a) and variation in the changes in Big4 share during their retreat from this market during 2009 to 2013 (panel 4b). Panel 4a highlights the relative dominance of the origination markets in the West as well as in Florida and parts of the East Coast as compared to Midwest and South. Panel 4b shows the county-level variation in the gap the Big4 left when they retreated the market from 2009 to 2013. While Figure 4 shows substantial regional variation, recall that the tests difference out these broad patterns and examine the changes in lender-class behavior within state, or in our later tests, within-lender variation controlling for county-level fixed effects.

We estimate the effect of the change in origination share of the Big4 from 2009-2013 on changes in the shares of other classes of lenders using the 2009 share of Big4 originations as an instrument.[11] Specifically, we estimate the following two-stage least squares regressions for each respective lender class:

[11] In untabulated results, we obtain similar IV estimates when using an alternative instrument where we predict the change in county share by multiplying the initial share by the national average change in Big4 share over the time period.

$$\Delta Share^{Big4}_{county} = \theta Share^{09Big4}_{county} + \zeta_{stateFE} + \Gamma X_{county} + \eta_{county} \tag{3}$$

$$\Delta Share^{LenderClass}_{county} = \psi \left(\Delta \widehat{Share^{Big4}_{county}} \right) + \xi_{stateFE} + \Lambda X_{county} + \epsilon_{county} \tag{4}$$

Table 6 presents the results. The first stage regression is strong with an F-statistic over 500 (see also its graphical representation of the first stage in Figure 3). Column (1) indicates that a one-s.d. decrease in $\Delta Share^{Big4}_{county}$ corresponds to a 5.0pp increase in the origination share of small banks, which is substantial compared with their initial (2009) average share of 34% originations. Again, shadow banks and fintech lenders (columns 2 and 3) are responsive to these local changes, but the effect is economically much smaller. This table also echoes the earlier results in that the large banks and credit unions are virtually insensitive to the change (columns 4 and 5).

4.4 Market Shares versus Raw Loan Growth

Examining relative market shares allows us to study the interactions of different lender classes while abstracting from broad changes in the size of the market. However, we also can examine differential raw loan growth across lender classes. This allows us to examine whether, for example, small banks are passively capturing market share as the Big4 retreat (with no growth in these areas), or whether they are actively responding by increasing their lending in absolute terms in these areas. Table 7 presents the IV results where the 2009 Big4 share is used as an instrument for Big4 growth. Column (1) shows that small banks are indeed expanding most strongly in areas vacated by the Big4. A one-s.d. lower Big4 growth (7.8pps, which, with mean Big4 growth of -5.7%, sums to a growth rate of -13.5%) leads to 9.3pps higher growth rate for small banks (whose mean county lending growth is -1.6%). The other lender classes are also growing in these areas, but the effect is more muted relative to the small banks.

4.5 Within-Lender Reallocation

The exclusion restriction in our IV tests requires that the Big4 2009 *level* of county share of mortgage originations is related to the 2009-2013 *change* in the small-bank county share of originations only through its effect on the 2009-2013 change in Big4 Share. Because we can never formally test the IV's exclusion restriction, there may still be concerns about time-varying, county-specific unobserved heterogeneity driving our results - for example, there could be unobserved, county-level variation in trends that both determined the 2009 Big4 share and also cause post-crisis small bank mortgage lending to increase.[12] There also may be concerns that bank-specific unobserved heterogeneity could be influencing the results. In this portion of the analysis, we address both potential issues by investigating at a finer, lender×county level to examine within-*lender* (not lender-class) responses to the Big4 retreat while controlling for county-specific and lender-specific heterogeneity. Specifically, we examine whether individual lenders tend to adjust their allocation of mortgage lending activity (i.e., lending growth) according to geographical variation in exposure to the Big4 retreat within their own lending footprint while also controlling for county fixed effects.

We estimate the following regression with subscripts representing lender l, county c, lending class g:

$$\Delta \log(loans)_{c,l,g}^{2009-2013} = \Theta_g \left[(\Delta Big4\ Share)_c^{2009-2013} \times \Gamma_g \right] + \delta_c + \lambda_l + \epsilon_{c,l,g} \tag{5}$$

The dependent variables ($\Delta \log(loans)_{c,l,g}^{2009-2013}$) is loan growth for the bank in a particular county during 2009-2013, and the key parameters of interest are the elements of Θ_g, which represent the average sensitivity of lenders in lender class g to county-level changes in Big4

[12] This unobserved variable would also have to have explanatory power even after controlling for the demographic and banking market characteristics we include in these tests.

share. Importantly, this regression includes both county fixed effects δ_c and lender fixed effects λ_l. These fixed effects can rule out some important alternative hypotheses. The county fixed effects absorb any county-level changes in demand, house prices, demographics, or overall economic prospects during our sample period. The lender fixed effects capture lender-specific drivers of changes in mortgage lending activities including shocks to the bank's capital, regulatory pressure, or overall commitment to mortgage lending. To ensure we capture economically meaningful changes, these tests include all individual lender-county observations in which the lender has originated a minimum of ten loans either in 2009 or 2013.

Column (1) of Table 8 presents the results. The negative coefficients on each of the lending class interaction terms (the level effect of the lending class is subsumed by the lender fixed effects) indicate that individual lenders within each lender class experienced relatively higher loan growth in areas with larger declines in the share of Big4 originations. For counties with a one-s.d. larger decrease in Big4 share, the within-lender relative increase in lender-county loan growth ranges from a high of a 24pps increase ($-100 * [e^{-0.279} - 1]$) for small banks down to around a 15pp increase for large banks and credit unions. These OLS estimates indicate a strong within-lender reallocation, with the highest sensitivities for small banks.

Similar to the county-level analysis earlier, we now instrument for the *change* in Big4 share with the 2009 *level* of Big4 share. This entails instrumenting each of the interaction terms with an interaction of the 2009 share of Big4 and group membership indicator variable. Column (2) of Table 8 presents the results, including the first-stage F-statistic, which indicates a strong first stage. While the magnitudes and statistical significance of the within-lender estimates decline for all other classes, the effect on small banks reallocation remains statistically and economically significant. Within the average small bank, counties in their footprint that have a one-s.d. decrease in Big4 share of the county mortgage origination market has an approximately 27pp ($-100 * [e^{-0.326} - 1]$) higher loan growth from 2009 to 2013, which is about a 5% compound annual rate, than in counties that experience the overall mean change in Big4 share. We discuss columns (3) and (4) in Section 7.

In sum, despite aggregate patterns of the Big4 have decline matched by nonbanks growth, our county-level results show that small banks are *locally* most responsive to changes in the Big4 share. These facts together paint a nuanced, but more complete picture of the massive reallocation of the supply of credit during the post-crisis period. In the next section, we examine some potential explanations for why small banks are more responsive than the shadow banks or fintech lenders.

5 Why small banks?

Despite regulatory and technological headwinds, why are small banks locally responding more strongly to the Big4 retreat relative to shadow banks and fintech? The strong reallocation of lending from the largest banks to small banks can be driven by credit demand-side or credit supply-side forces. We examine differential sensitivity to the Big4 withdrawal of specific county-level characteristics to measure the importance of each influence below.

5.1 Demand-Side: Preferences for Banks

There may be credit-demand-side factors that drive the higher relative sensitivity of small banks to the Big4 withdrawal as compared to nonbanks (shadow banks and fintech lenders). Our primary factor of interest on the credit-demand side is consumer preferences to borrow from a bank.

For a variety of reasons, many potential borrowers would rather borrow from a bank than from a shadow bank or fintech lender. Among other reasons, many borrowers may have a long-term borrowing relationship (Boot, 2000) or a higher level of familiarity, comfort, or trust in dealing with a bank as compared to a shadow bank or fintech lender (e.g., see Merton and Thakor, 2018). Borrowers may also prefer the additional flexibility in loan offerings that banks may have since they have the ability to carry loans on their balance sheet. Some borrowers prefer borrowing from banks because banks can bundle services (e.g., free premium checking services) or simplify bill payments. Others may derive comfort in knowing that if there is difficulty in the future, the bank may be better equipped or willing to work for a good outcome during renegotiation, if necessary. While these characteristics fit most banks, they are particularly strong for small banks. If many borrowers have a preference for borrowing with a bank, then it follows that the increase of small banks in response to the Big4 withdrawal (i.e., within-traditional-bank substitution) will be stronger in areas where the preference for bank borrowing is higher.

While these ideas may be intuitive, measuring the degree of preference for borrowing from a bank over a nonbank is challenging. We create a novel, county-level measure (*PreferBanks*) to proxy for this preference. We begin by computing conversion rates for loan applications submitted to banks and nonbanks. Specifically, the county-level bank conversion rate for each group is the number of loans originated in the county by that group divided by the number of loans that were not denied. For example, consider a county with 10,000 loan applications to banks where 2,000 are denied by the banks, 6,000 are eventually originated, and the remaining 2,000 are neither denied nor originated. This would yield a bank conversion rate of 75% (6,000/8,000) of their non-denied loans in that county. Similarly, if there were 10,000 loan applications to nonbanks with 3,000 denied, 3,500 are eventually originated, and 3,500 neither denied nor originated, this would yield a nonbank conversion rate of 50% (3,500/7,000) of their non-denied loans in the county. We take the 2001-2009 average of the annual difference in these two rates in the county as our measure for a county's long-term preference for borrowing from a bank over a nonbank:

$$PreferBanks_{county} = \frac{\#originations_{Banks}}{\#application\ not\ denied_{Banks}} - \frac{\#originations_{nonbanks}}{\#application\ not\ denied_{nonbanks}} \quad (6)$$

Figure 5 graphically presents the densities of the respective conversions rates in panel 5(a), and the density of $PreferBanks_{county}$ in panel 5(b). The figure shows that the measure is well-behaved, with substantial cross-sectional variation in relative preferences for banks with a mean of 26 pps and 10%ile-90%ile range of 14pps-39pps. Figure 6 presents the geographical variation in the measure, with the highest levels of $PreferBanks_{county}$ in the middle of the country and along upper Appalachia and Pennsylvania. Figure 6a presents the overall measure, and Figure 6b presents the state-adjusted measured (de-meaning by state), which is effectively the variation we will use in the regression estimates including state fixed effects.

We estimate the relative sensitivity of lender-class response to the Big4 withdrawal to the county-level preference for borrowing from banks by estimating 2SLS regressions by including $PreferBanks_{county}$ and its interaction with the change in Big4 share (with relevant first stage regression for each).[13] Specifically, we estimate the following 2SLS system including the earlier controls and fixed effects in C:

$$\begin{aligned}\Delta Share^{Big4}_{county} =& \beta_1 Share^{09Big4}_{county} + \gamma_1 PreferBanks_{county} \\ &+ \kappa_1 (Share^{09Big4}_{county} \times PreferBanks_{county}) + \Upsilon_1 C_{county} + \upsilon_{county}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta Share^{Big4}_{county} \times PreferBanks_{county} =& \beta_2 Share^{09Big4}_{county} + \gamma_2 PreferBanks_{county} \\ &+ \kappa_2 (Share^{09Big4}_{county} \times PreferBanks_{county}) + \Upsilon_2 C_{county} + \eta_{county}\end{aligned} \tag{8}$$

$$\begin{aligned}\Delta Share^{LenderClass}_{county} =& \psi \left(\Delta \widehat{Share^{Big4}_{county}} \right) + \phi PreferBanks_{county} \\ &+ \rho (\Delta Share^{Big4}_{county} \widehat{\times PreferBanks_{county}}) + \Gamma C_{county} + \epsilon_{county}\end{aligned} \tag{9}$$

Table 9 presents the results estimated for small banks (columns 1-3), shadow banks (columns 4-6), and fintech lenders (columns 7-9). Columns 1-3 show that small banks'

[13] We provide the reduced form estimates in Appendix Table A.3

increase in share is strongest where the Big4 retreated. The coefficients of interest in these tests, though, are the interaction between the change Big4 share and preference for banks. Column 3, which uses an indicator variable equal to one for banks with above-average *PreferBanks*, indicates that a one-s.d. larger drop in Big4 leads to a 3.0pps increase in small bank share for below-median *PreferBanks*, but a substantially larger response of 6.0pps (3.0+3.0) in counties with above-median *PreferBanks*. The estimates for shadow banks and fintech lenders do not provide evidence of such differential sensitivity. These results suggest that borrowers' preference for borrowing from a bank (as compared to nonbank) is an important credit-demand-side driver of the small banks strong advance where the Big4 withdrew from the mortgage origination market.

5.2 Supply-Side: Securitizable Loans

A fundamental difference in banks lenders and nonbank (shadow bank or fintech) lenders is balance sheet capacity (Buchak et al., 2018b). By the construction of their business model, nonbanks act primarily as a pass-through to the government-sponsored securitization markets (Fannie Mae, Freddie Mac) and government-insured mortgages (FHA, VA). Collectively, we call these government-supported loan programs (GSLP). As a result, they have very limited scope to make loans that do not conform to the relevant standards. This would include loans of sufficiently low credit quality (at least on the hard dimensions required by the GSLPs) and loans that are above the GSLP conforming loan limits.[14] We compute the long-term average county-level share of loans that are sold through government programs and consider this average as a cross-sectional measure of the "securitizability" of the typical loans in the area. Specifically, we compute the long-run (2001-2009) average of the share of loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac for each county.[15] Because nonbanks keep

[14]Similarly, this notion relates to the literature focusing on the comparative advantage of banks, and smaller banks in particular, in collecting and making use of soft information, typically in the context of small business lending (Stein, 2002; Berger et al., 2005, 2017).

[15]HMDA reports whether the loan was sold to these entities during the calendar year. These numbers will be an underestimate of the total sold because loans made late in the year and then sold the following

virtually no loans on their balance sheet while small banks keep a substantial share of loans on their balance sheet (much more than large banks or the Big4), this supply-side difference in availability of securitization across counties predicts that small banks may respond stronger to Big4 withdrawal in areas with relatively lower securitizability. We estimate the relative sensitivity of lender-class response to the Big4 withdrawal to the county-level securitizability by interacting the change in Big4 share with $GSLP_{county}$ using the same framework as we used in the 2SLS regression (equations 7-9) earlier.[16]

Table 10 presents the results. For each lender class, we present the estimates without control variables, with control variables, and then using an indicator variable equal to one for counties with GSLP greater than the median for ease of interpretation. Columns 1-3 shows that counties with a lower historical share of securitized loans experience a greater increase in small bank share, and that increase is most pronounced where the Big4 retreated. In particular, column 3 indicates that a one-s.d. larger drop in Big4 leads to a 6.1pps increase in small bank share for below-median GSLP activity, but a smaller response of 3.9pps (6.1-2.2) in above-median GSLP counties. On the other hand, the estimates for shadow banks and fintech lenders provide no evidence of such differential sensitivity. The relatively stronger share growth for small banks in areas where balance sheet lending is more often necessary suggests that the institutional features of the supply side of credit, namely government supported securitization markets, are an important driver of our findings.

5.3 Horse Race

In our next test, we include both the supply- and demand-side factors and their interaction with the change in Big4 Share in a single regression model. We note that this puts a great deal of strain on our instrument (2009 Big4 share) as its variation will be used as the source

calendar year will be counted as "not sold."

[16] We provide the reduced form estimates in Appendix Table A.4

of variation for the change in Big4 share as well as each of the interaction terms.[17] Table 11 presents the results. Column 1 uses the continuous measures of the need for balance sheet capacity (low GSLP) and preference for banks (*PreferBanks*) and finds results directionally consistent with the earlier results, but the differential sensitivity of small banks to the Big4 retreat with areas of differing GSLP is not statistically significant. The estimates in column 2 use the discrete measures (above- and below-median) of the supply and demand factors and find both factors to be statistically and economically significant, with each factor having an independent influence on the small bank advance where the Big4 retreated. Similar to the earlier tests, we do not find differential sensitivity to these factors for shadow banks (columns 3-4) or fintech lenders (columns 5-6).

6 Redistributive Consequences

So far, we have argued that small banks are an important countervailing source of mortgage credit following the Big4 retreat. The composition of credit supply is important for issues including access to credit and systemic risk (D'Acunto and Rossi, 2017; Gete and Reher, 2018; Kim et al., 2018). Here, we use the framework from D'Acunto and Rossi (2017) to examine whether small banks mitigate the redistributive effects attributed to the largest lenders' withdrawal.

D'Acunto and Rossi (2017) show that the distribution of mortgage loan sizes changes from 2011 onwards after the passage of Dodd-Frank. Since the regulations particularly affected the behavior of larger banks, they show that the average size of loans below the conforming limit of $417,000 decreases in areas with greater presence of large banks. On the other hand, the size of jumbo loans, which are made to relatively wealthier households, increases in those areas. D'Acunto and Rossi (2017) argue this regressive credit redistribution may have contributed to an increase in wealth inequality since 2011. Does the relative presence of small

[17] We provide the reduced form estimates in Appendix Table A.5

banks versus nonbanks mitigate the redistributive effect?

If the redistribution is purely driven by the relatively higher fixed cost for all banks to originate a loan, we might expect the effect to be stronger where more small banks are present relative to nonbanks (whose origination costs were largely unaffected by banking regulation). However, if the channels documented in the previous sections remain relevant, we may expect small banks, rather than nonbanks, to be a closer substitute for the loans foregone by the Big4. In that case, small bank presence should mitigate redistributive effects.

We estimate regressions similar D'Acunto and Rossi (2017) by using the log of loan size for all originated first-lien, owner-occupied, purchase loans in HMDA as the dependent variable. For independent variables, we use the Big4 rather than top 20 banks, and we introduce an additional term to capture the ratio of small bank to nonbank lending in the county. We interact the ratio of small bank shares to non-bank shares with the Big4 share and Post2011 as shown below, where ψ is the parameter of interest:

$$\begin{aligned} \mathit{Log(LoanAmount)}_{i,c,t} =& \beta \left(\mathit{Share}_{c,t}^{Big4} \right) + \delta \left(\mathit{Share}_{c,t}^{Big4} \right) \times (\mathit{Post2011}_t) \\ &+ \phi \left(\frac{\mathit{SmallBank}_{c,t}}{\mathit{NonBank}_{c,t}} \right) + \rho \left(\frac{\mathit{SmallBank}_{c,t}}{\mathit{NonBank}_{c,t}} \right) \times (\mathit{Post2011}_t) \\ &+ \psi \left(\mathit{Share}_{c,t}^{Big4} \right) \times (\mathit{Post2011}_t) \times \left(\frac{\mathit{SmallBank}_{c,t}}{\mathit{NonBank}_{c,t}} \right) \\ &+ \zeta_c + \lambda_t + \Gamma X_{i,c,t} + \epsilon \end{aligned} \tag{10}$$

Table 12 presents the results, with each column representing different loan size categories: <\$100K, \$100K - \$200K, \$200K - \$417K (the conforming loan limit), \$417K - \$700K, and>\$700K. The first row in Table 12 confirms the finding in D'Acunto and Rossi (2017) (note that we use a shorter time period and use the Big4 rather than top 20 banks). Since 2011, areas with a larger Big4 presence have decreased loan sizes in categories below the conforming limit (especially columns 2 and 3) but substantially increased loan sizes in the largest jumbo loan categories (column 5). When we estimate the triple interaction ψ using the ratio of small bank to non-bank share, we find a positive, significant coefficient for loans in the range of \$200K - \$417K (below the conforming loan limit). This result complements the finding in D'Acunto and Rossi (2017) by showing the presence of small banks mitigates the redistributive effects of the regulation on large banks. While a full analysis is beyond the scope of our paper, this result reinforces the notion that the composition of the supply of credit matters, and that small banks are able to partially offset the effects of withdrawal by the largest banks.

7 Granularity in Mortgage Market Fluctuations

In this section, we examine the far-reaching impact on a sizable market, emanating from the withdrawal decision of a single player (Bank of America). We are motivated by Gabaix (2011)'s "granular hypothesis," which argues that aggregate fluctuations can be understood by analyzing the behavior of large firms in any industry. While we know that the fate of large banks during bad times can have substantial, even financially catastrophic, effects during times of crisis, this study provides evidence of outsize influence even during relatively normal times.

Bank of America (BoA) had the sharpest withdrawal of the Big4 during the sample period. Stinging from several post-crisis lawsuits, BoA decided to reduce drastically their mortgage lending activities. In addition to the fines and judgments for their own behavior during the run-up to the crisis, they were responsible for the past behavior of Countrywide, who BoA acquired in 2008 for \$4 billion in stock. As of 2012, the cost to BoA for Countrywide's practices was already at \$40 billion,[18] and the sum has only increased since then.

Examining BoA's sharp retreat (6.5% to 2.5% for the average county) in response to these costs provides a nice setting to study the outsize influence of a single player in this

[18]https://dealbook.nytimes.com/2012/10/25/tallying-the-costs-of-bank-of-americas-countrywide-nightmare/

market. We begin by focusing on the response of small banks to variation in BoA withdrawal using the base specification (1) from earlier, replacing the changes in Big4 share with the changes in BoA share. In column (1) of Table 13, we find that a one-s.d. larger drop in BoA share ($\Delta Share^{09-13}_{BoA}$), which is about 4pps, corresponds with a 2.5pps larger increase in small bank share. Using the 2009 BoA share as an instrument, column (2) shows a similar effect or 2.1pps for the IV as compared to the OLS in column (1).[19]

BoA acquired Countrywide, the top originator in the country, in 2008 to substantially increase their mortgage origination business. Despite the increases in market share, the acquisition proved financially disastrous as Countrywide practices came to light. Much of BoA's withdrawal can be linked to pulling out of areas of higher acquired shares through Countrywide. Thus, we now use Countrywide's 2007 (i.e., pre-acquisition) county share of originations ($Share^{07}_{CW}$) as an alternative instrument for $\Delta Share^{09-13}_{BoA}$. Column (3) of Table 13 shows that we find similar results, and that the F-statistic of about 85 showing the strong first-stage relationship between $Share^{07}_{CW}$ and $\Delta Share^{09-13}_{BoA}$. A one-s.d. larger change in BoA share ($\Delta Share^{09-13}_{BoA}$) corresponds with a 3.2pps larger increase in the small bank share of mortgage originations.

Columns (4)-(7) present the analysis for shadow banks and fintech lenders. Similar to the earlier baseline analysis examining the response to the retreat of all of the Big4, these lenders increase their shares in counties where BoA retreated, but the economic magnitudes of the sensitivity are smaller at about 0.9-1.2pps for shadow banks and 0.2pp-0.4pp for fintech lenders. So while both small banks and nonbanks made gains where BoA withdrew, the sensitivity of the small banks is 2-3 times larger than shadow banks and almost 10 times larger than fintech lenders.

[19]The strength of the F stat, which indicates that the level in 2009 is an extremely strong predictor of the amount of the ensuing withdrawal, shows how widespread the retreat was for BoA.

8 Conclusion

Following post-crisis regulatory fines and increase in regulatory burden, the Big4 banks made a substantial retreat from the mortgage markets. During the same time period, shadow banks and fintech lenders surged in their share of aggregate mortgage lending. The market changes, however, are more nuanced than simply a transfer of share between these two groups of lenders. Amidst this widespread rise in shadow banks and fintech lenders, we present new results that small banks have been a strong countervailing supplier of credit in the areas where the Big4 banks had the largest pullback of lending. We find that small banks are more than twice as sensitive to Big4 retreat as shadow banks and about four times as sensitive as fintech lenders. Consistent with these county-level results, we provide evidence of a significant within-lender reallocation of lending towards counties of Big4 retreat, with the strongest reallocation happening for small banks.

We find that both supply- and demand-side forces contribute to these changes. Using a novel measure of borrowers' preferences, we also find that counties with borrowers who have shown a stronger historical preference for borrowing from banks over nonbanks have the strongest small-bank response to the Big4 retreat. We also show that counties with borrowers who have a higher need for on-balance-sheet financing, which can be provided by small banks but not nonbanks, have a stronger advance by small banks.

In sum, we present new empirical facts about the changing face of mortgage lending. Our results show the continuing importance and role of small banks, even in a period of increased bank regulation and rapid technological change. In light of recent work showing that the composition of mortgage credit supply has real effects, we provide some evidence that small banks may mitigate in part some of the adverse effects of the widespread retreat by the largest banks. Finally, we show how the (potentially idiosyncratic) market participation decisions of a single player amongst the too-big-to-fail (e.g., Bank of America), even in normal times, can have far-reaching effects through the reallocation of lending.

References

Abadie, Alberto, and Guido W Imbens, 2011, Bias-corrected matching estimators for average treatment effects, *Journal of Business & Economic Statistics* 29, 1–11.

Acharya, Viral V, Philipp Schnabl, and Gustavo Suarez, 2013, Securitization without risk transfer, *Journal of Financial Economics* 107, 515–536.

Adrian, Tobias, and Adam B Ashcraft, 2012, Shadow banking regulation, *Annual Review of Financial Economics* 4, 99–140.

Avery, Robert, Kenneth Brevoort, and Glenn Canner, 2007, Opportunities and issues in using HMDA data, *Journal of Real Estate Research* 29, 351–380.

Berger, Allen N, Christa HS Bouwman, and Dasol Kim, 2017, Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time, *Review of Financial Studies* 30, 3416–3454.

Berger, Allen N, Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein, 2005, Does function follow organizational form? Evidence from the lending practices of large and small banks, *Journal of Financial Economics* 76, 237–269.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2016, Relationship and transaction lending in a crisis, *The Review of Financial Studies* 29, 2643–2676.

Boot, Arnoud W. A., 2000, Relationship banking: What do we know?, *Journal of Financial Intermediation* 9, 7–25.

Boot, Arnoud WA, and Anjan V Thakor, 2000, Can relationship banking survive competition?, *The Journal of Finance* 55, 679–713.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018a, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018b, The limits of shadow banks .

Chen, Brian S, Samuel G Hanson, and Jeremy C Stein, 2017, The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets, Technical report, National Bureau of Economic Research.

Cortés, Kristle, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E Strahan, 2018, Stress tests and small business lending, Technical report, National Bureau of Economic Research.

D'Acunto, Francesco, and Alberto Rossi, 2017, Regressive mortgage credit redistribution in the post-crisis era .

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, 2019, The role of technology in mortgage lending, *The Review of Financial Studies* 32, 1854–1899.

Gabaix, Xavier, 2011, The granular origins of aggregate fluctuations, *Econometrica* 79, 733–772.

Gete, Pedro, and Michael Reher, 2018, Mortgage supply and housing rents, *The Review of Financial Studies* 31, 4884–4911.

Gilje, Erik P, 2017, Does local access to finance matter? Evidence from US oil and natural gas shale booms, *Management Science* .

Gorton, Gary, Andrew Metrick, Andrei Shleifer, and Daniel K Tarullo, 2010, Regulating the shadow banking system [with comments and discussion], *Brookings papers on economic activity* 261–312.

Hein, Scott E, Timothy W Koch, S Scott MacDonald, et al., 2005, On the uniqueness of community banks, *Federal Reserve Bank of Atlanta Economic Review* 90, 15–36.

Kim, You Suk, Steven M Laufer, Richard Stanton, Nancy Wallace, and Karen Pence, 2018, Liquidity crises in the mortgage market, *Brookings Papers on Economic Activity* 2018, 347–428.

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

Lux, Marshall, and Robert Greene, 2015, What's behind the non-bank mortgage boom, *Mossavar-Rahmani Center for Business and Government, Harvard Kennedy School* .

McCoy, Patricia A, and Susan Wachter, 2017, Representations and warranties: Why they did not stop the crisis, in Lee Fennell, and Benjamin Keys, eds., *Evidence and Innovation in Housing Law and Policy*, 289–321 (New York: Cambridge University Press).

Merton, Robert C, and Richard T Thakor, 2018, Trust in lending, *National Bureau of Economic Research Working Paper* .

Petersen, Mitchell A, and Raghuram G Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *The Journal of Finance* 49, 3–37.

Stein, Jeremy C, 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *Journal of Finance* 57, 1891–1921.

Stein, Jeremy C, et al., 2014, Regulating large financial institutions, *MIT Press Book Chapters* 1, 135–142.

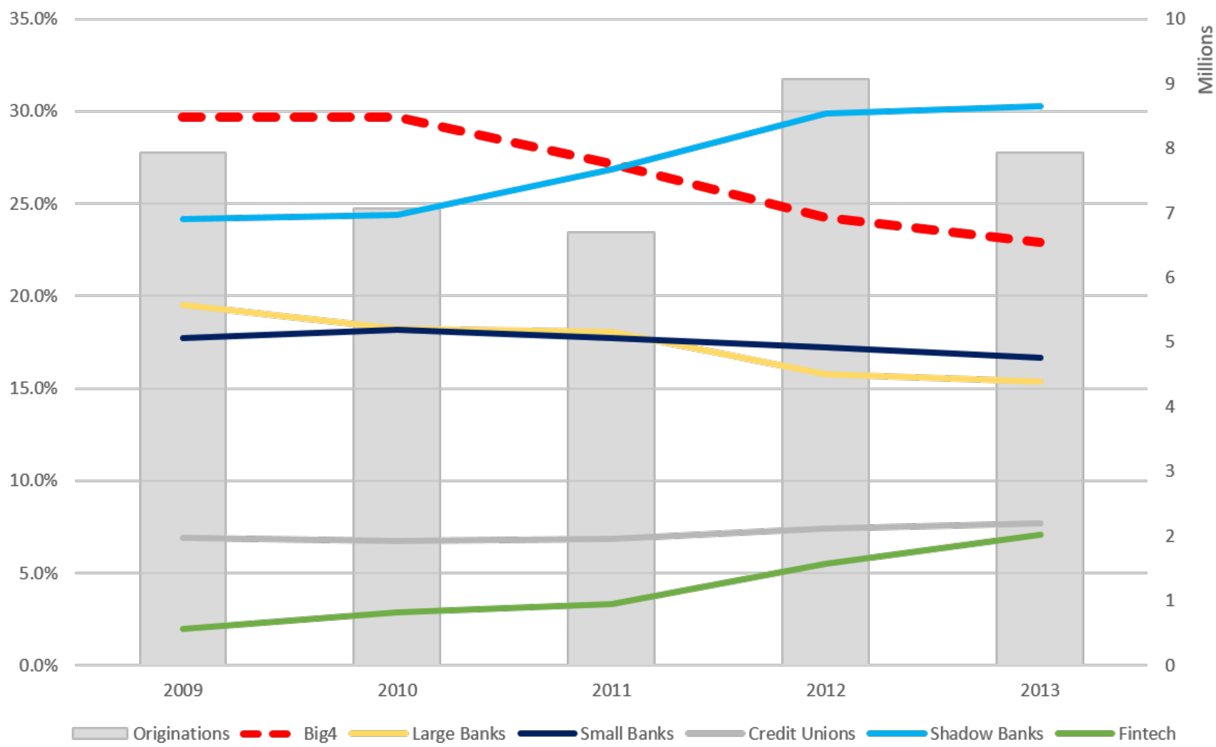


Figure 1: Aggregate Lending Shares Over Time
This figure presents the aggregate mortgage origination market shares for each lending class over time (left axis). *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between \$10 billion and \$1 trillion in 2011, and *Small Banks* includes banks with assets less than \$10 billion in 2011. The shaded bars represent the aggregate number of loans originated (millions, right axis) in the U.S. for our sample.

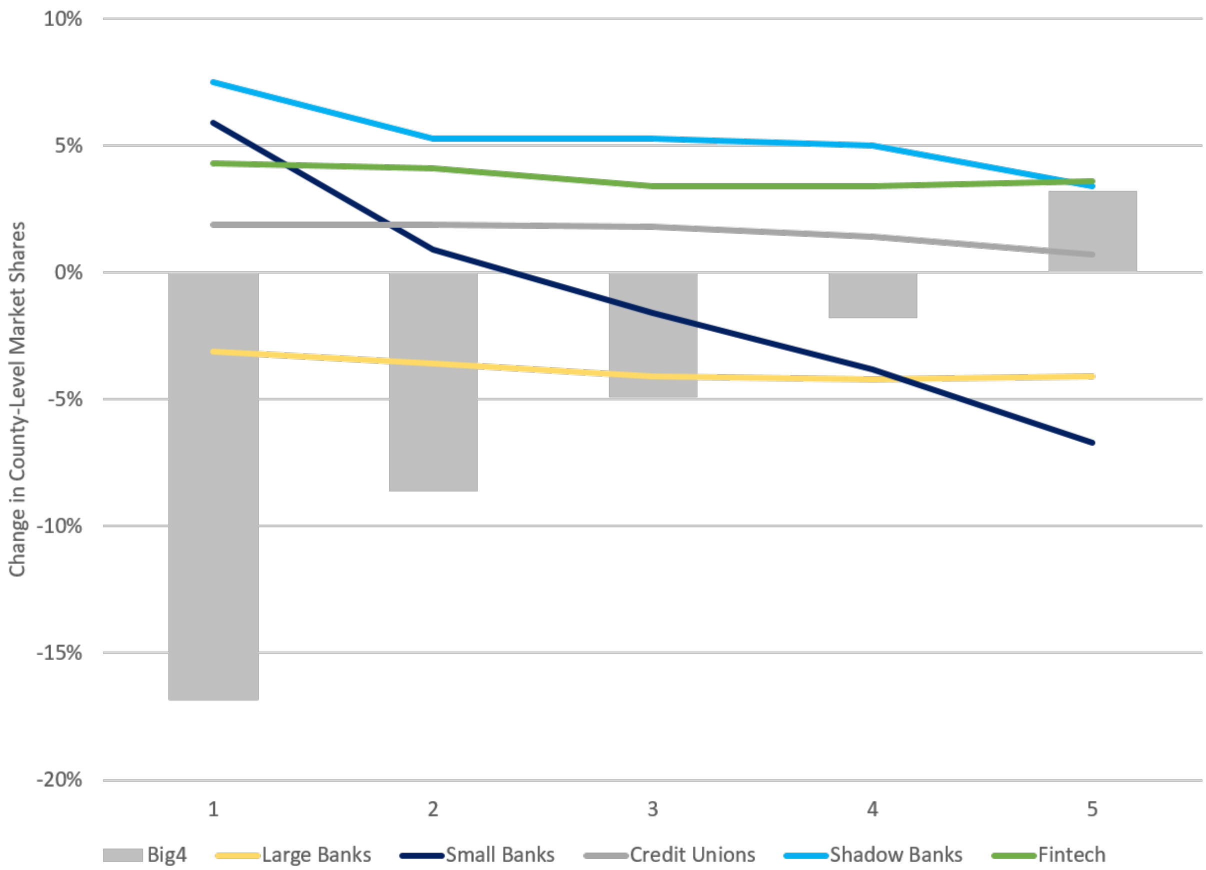


Figure 2: Change in County-Level Lender Composition
This figure presents the changes in county-level lender composition from 2009 to 2013. The bars represent the average county change in Big4 share divided into quintiles (1 has the largest drop to 5 has the largest increase). Each lender class is represented by lines which show their respective change in county-level market share for each Big4-change quintile. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, and *Small Banks* includes banks with assets less than $10 billion in 2011.

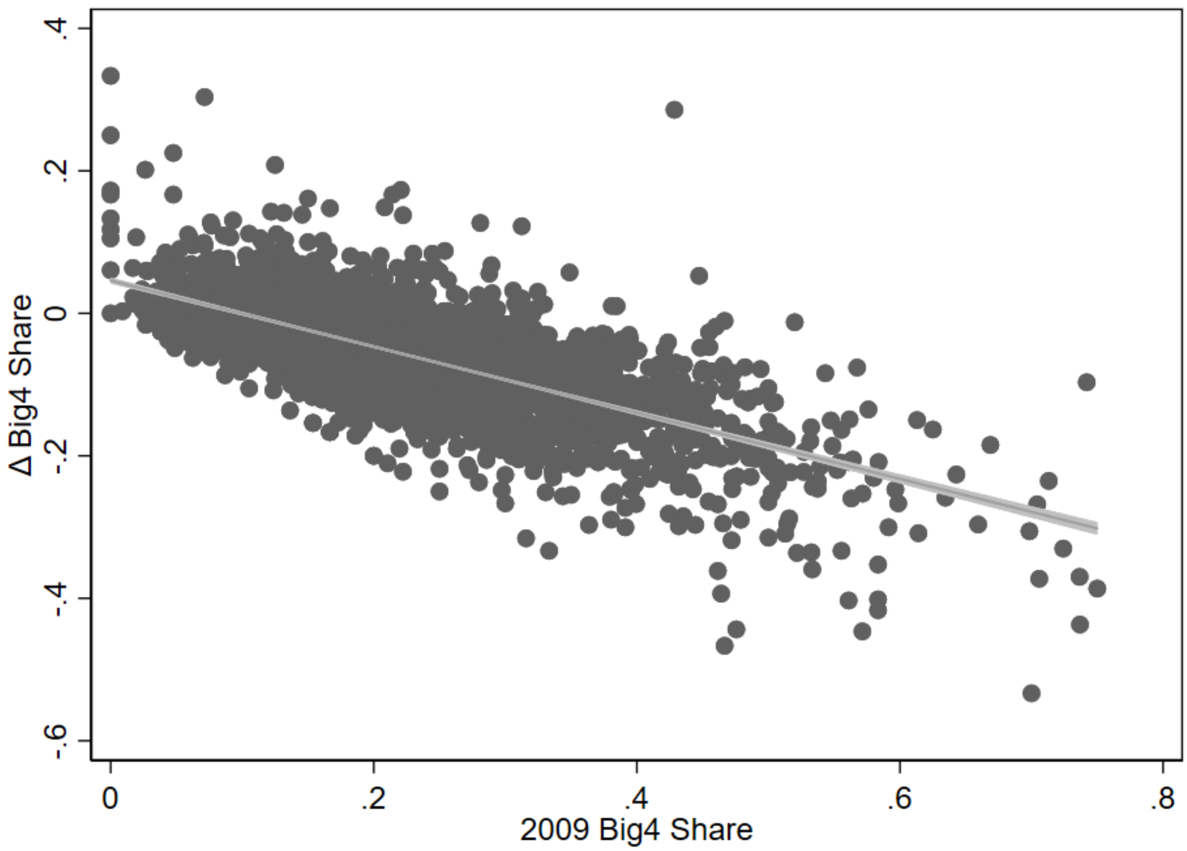
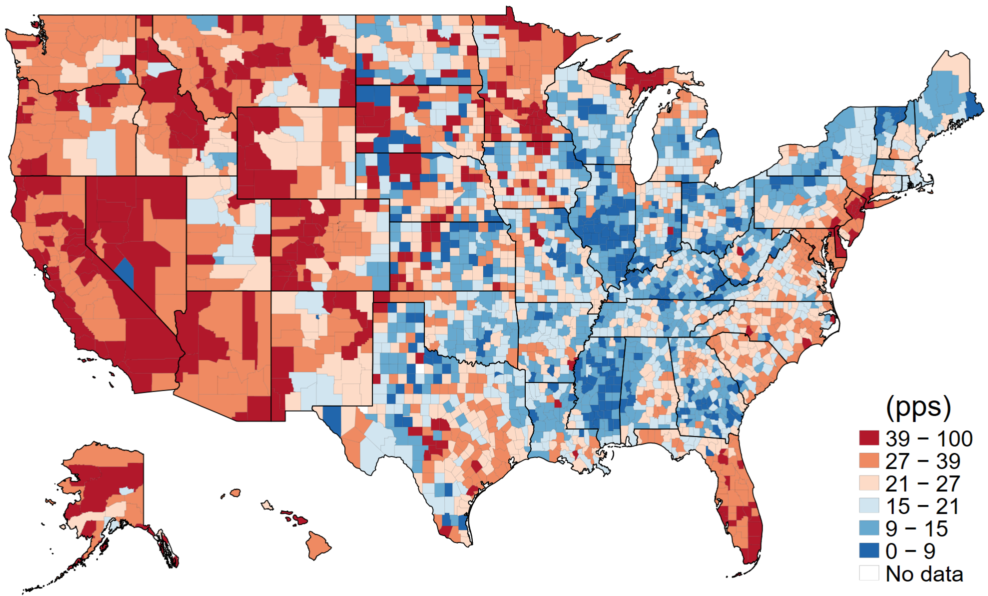
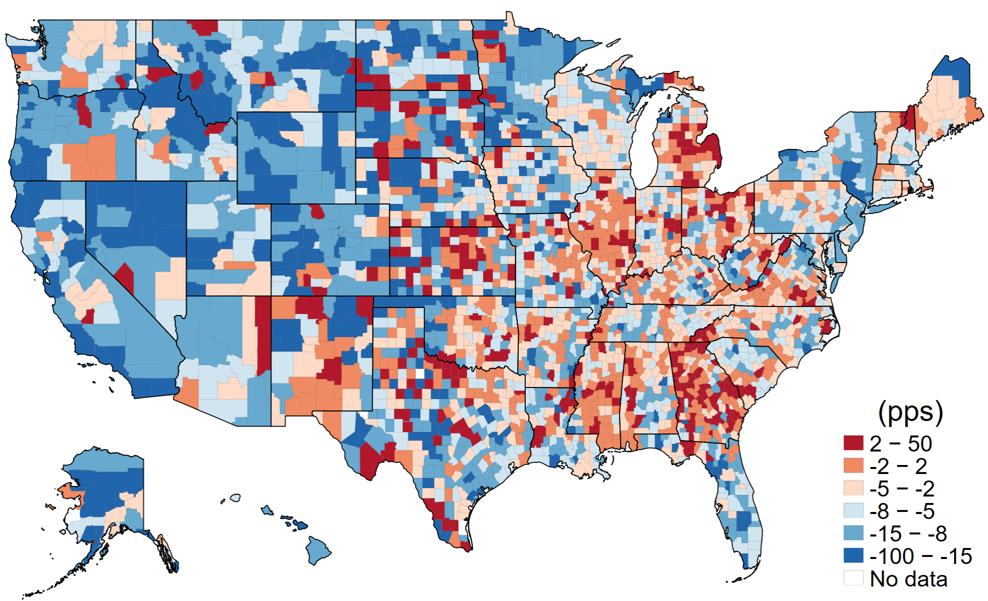


Figure 3: 2009 Big4 Share and 2009-2013 Big4 Share Change
This figure plots the changes in Big4 share for each county in the sample from 2009-2013 (y-axis) against the 2009 Big4 county share of mortgage originations. *Big4* includes Bank of America, Citi, JP Morgan, and Wells Fargo.

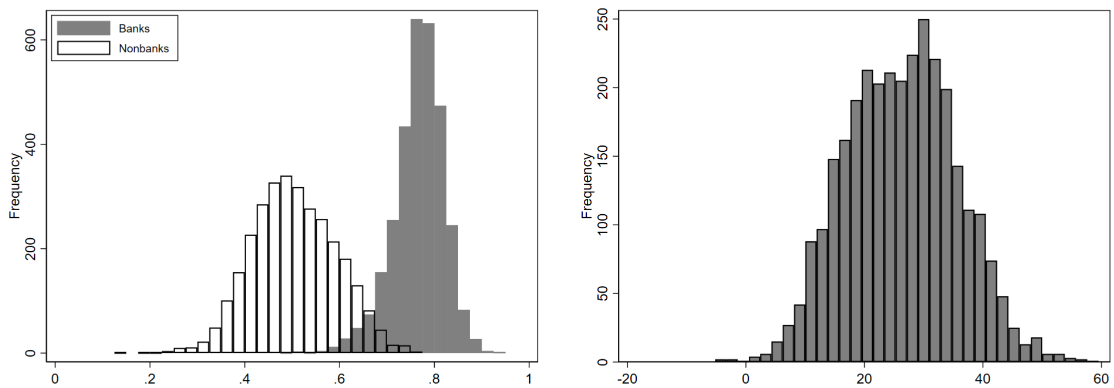


(a) 2009 Big4 Origination Share



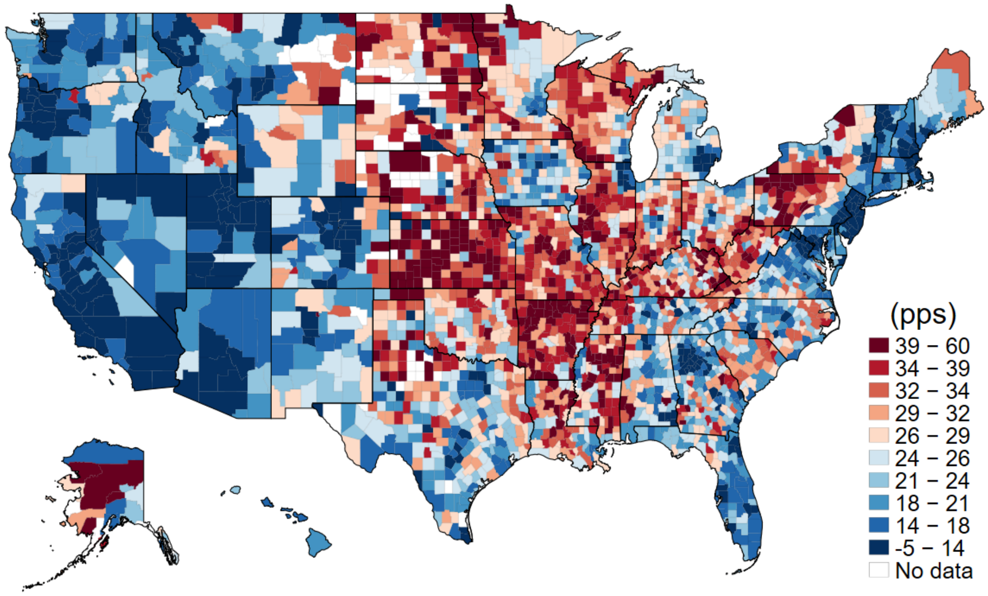
(b) Change from 2009 to 2013 Big4 Origination Share

Figure 4: 2009 Big4 Share and 2009-2013 Big4 Share Change
This figure presents the share of mortgages by the Big4 banks (Bank of America, Citi, JP Morgan, and Wells Fargo) in 2009 in Panel (a). Panel (b) plots the change in Big4 origination share from 2009 to 2013.

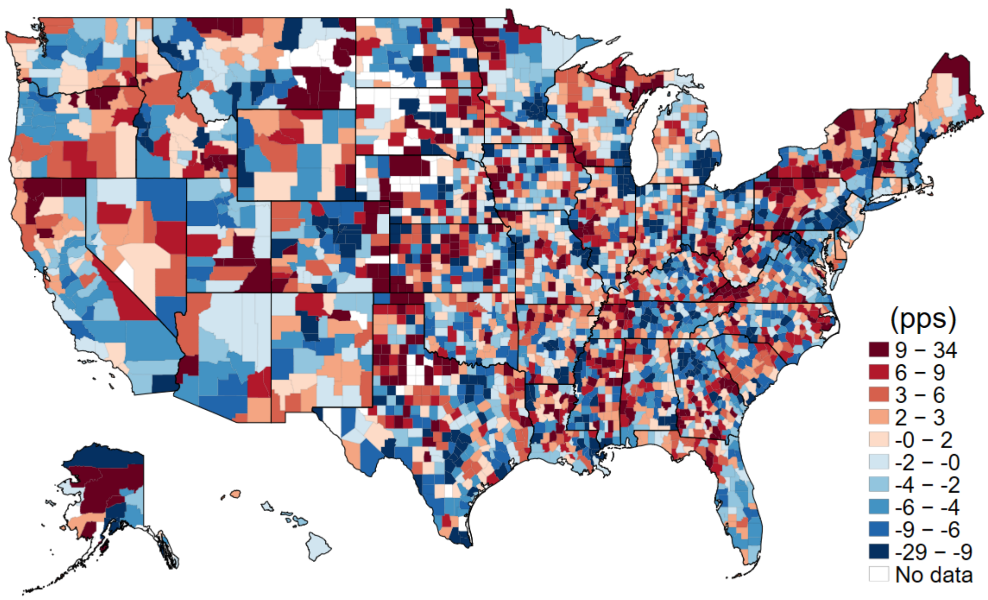


(a) Conversion Rates **(b)** Preference for Banks

Figure 5: Preferences for Banks over Nonbanks
This figure presents the loan origination conversion rates for banks and nonbanks Panel (a). Panel (b) plots the difference in the two rates, which is our measure of a county's preference for banks. We compute the conversion rates by dividing the number of loans originated in the county by that group by the number of loans that were not denied. We take the 2001-2009 average of the annual difference in these two rates in the county as our measure for a county's preference for borrowing from a bank over a nonbank.



(a) Overall



(b) State-Adjusted

Figure 6: Preference for Banks: Raw and State-Adjusted

This figure presents the geographical variation in our measure of a county's preference for banking services. Panel (a) refers to the overall measure and Panel (b) presents the measure de-meaned by state.

Table 1: County Summary Statistics

This table presents county-level summary statistics for 2009. *Population* is the population in thousands, *Minority* is the nonwhite share of the population, *Income* is the per capita income in thousands, *Subprime* is the share of the population with FICO below 660, and *HHI* is the county banking competition based on deposits. *Banks (physical)* is the number of unique banks with a branch in the county, *Banks (lending)* is the number of unique banks with mortgage lending activity in the county, and *Nonbanks (lending)* is the number of unique nonbanks (shadow banks and fintech) with mortgage lending activity in the county. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a).

	mean	sd	min	p25	p50	p75	max	N
Panel A: County Characteristics								
Population	101.32	317.71	0.66	12.36	27.20	69.60	9787.40	2986
Minority	0.21	0.19	0.01	0.06	0.14	0.32	0.97	2986
Income	32.72	7.90	14.55	27.70	31.41	35.90	129.16	2986
Subprime	0.33	0.09	0.08	0.26	0.32	0.39	0.71	2986
HHI	0.30	0.19	0.05	0.17	0.25	0.38	1.00	2986
Banks (physical)	9.10	9.81	1.00	4.00	6.00	11.00	158.00	2986
Banks (lending)	51.27	37.54	4.00	27.00	41.00	63.00	399.00	2986
Nonbanks (lending)	51.30	44.54	1.00	20.00	38.00	68.00	303.00	2986
Panel B: 2009 County Mortgage Lending Shares								
Big4	0.22	0.12	0.00	0.13	0.21	0.29	0.75	2986
Small Banks	0.34	0.21	0.00	0.16	0.31	0.48	0.94	2986
Shadow Banks	0.17	0.1	0.00	0.09	0.15	0.23	0.67	2986
Fintech	0.02	0.02	0.00	0.01	0.02	0.03	0.27	2986
Large Banks	0.19	0.11	0.00	0.10	0.17	0.26	0.73	2986
Credit Unions	0.06	0.07	0.00	0.02	0.04	0.08	0.58	2986

Table 2: Variation in Big4 Withdrawal and Lender Composition

This table presents the average change in county-level mortgage origination shares (in percentage points) for each lender class from 2009-2013. The counties are classified into quintiles according to the size of the change in Big4 Share over this time period. The bottom of the table presents the overall average and the difference from the 5th to 1st quintile. *Big4* represents Bank of America (*BoA*), Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* include nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a).

	2009-2013 County-level Share Change (pps)					
Big4 Change Quintile	Big4	Small Banks	Shadow Banks	Fintech	Large Banks	Credit Unions
1 (largest drop)	-16.8	5.9	7.5	4.3	-3.1	1.9
2	-8.6	0.9	5.3	4.1	-3.6	1.9
3	-4.9	-1.6	5.3	3.4	-4.1	1.8
4	-1.8	-3.8	5.0	3.4	-4.2	1.4
5 (largest increase)	3.2	-6.7	3.4	3.6	-4.1	0.7
Average 2009-2013 Change	-5.8	-1.1	5.3	3.8	-3.8	1.6
Difference (5-1)	20.0	-12.6	-4.1	-0.7	-1.0	-1.2

Table 3: Variation in Big4 Withdrawal and County Characteristics

This table presents the mean [median] county 2009 characteristics according to the amount of change in county-level Big4 mortgage origination shares from 2009-2013. *Big4* represents Bank of America (*BoA*), Citi, JP Morgan, and Wells Fargo, *Population* is the 2009 population in thousands, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income in thousands, *Subprime* is the 2009 share of the population with FICO below 660, and *HHI* is the 2009 county banking competition base on deposits.

Big4 Change Quintile	Population	Minority	Income	Subprime	HHI
1 (largest drop)	102.23	0.21	34.55	0.30	0.35
	[18.47]	[0.14]	[32.89]	[0.28]	[0.27]
2	135.68	0.22	34.18	0.32	0.28
	[34.08]	[0.15]	[32.36]	[0.3]	[0.23]
3	118.45	0.21	33.18	0.33	0.29
	[32.39]	[0.13]	[32.27]	[0.32]	[0.22]
4	82.68	0.19	31.32	0.34	0.28
	[29.73]	[0.11]	[30.51]	[0.34]	[0.23]
5 (largest increase)	51.01	0.24	30.44	0.35	0.37
	[19.77]	[0.17]	[29.46]	[0.35]	[0.29]

Table 4: Cross-Sectional Heterogeneity in Response to the Big4 Retreat

This table presents OLS estimates from the regressions of changes in the county-level share of mortgage originations for each lender class from 2009-2013 on the county-level change in Big4 share of originations during this time period. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between \$10 billion and \$1 trillion in 2011, *Small Banks* includes banks with assets less than \$10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). The dependent variables are the respective county-level change in share from 2009-2013 for each lender class, and $\Delta Share^{Big4}_{county}$ represents the change for the Big4. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. $\overline{\Delta Share^{LenderClass}_{county}}$ represents the mean of the dependent variable. Standard errors are clustered by MSA.

	(1) Small Banks	(2) Shadow Banks	(3) Fintech	(4) Large Banks	(5) Credit Unions
$z\Delta Share^{Big4}_{county}$	-0.047***	-0.017***	-0.002***	-0.000	-0.004***
	(<0.01)	(<0.01)	(<0.01)	(0.77)	(<0.01)
zln(Population)	-0.015*	0.016**	-0.001	0.002	-0.003
	(0.06)	(0.02)	(0.75)	(0.64)	(0.36)
zMinority	0.002	-0.005	0.002*	-0.004	0.003
	(0.70)	(0.27)	(0.06)	(0.14)	(0.17)
zIncome	0.001	0.001	-0.002	0.003	-0.002
	(0.75)	(0.79)	(0.16)	(0.29)	(0.28)
zSubprime	-0.015**	0.010**	-0.002	0.008***	-0.000
	(0.02)	(0.03)	(0.35)	(0.01)	(0.87)
zHHI	0.005	-0.009**	0.003*	0.003	-0.001
	(0.22)	(0.01)	(0.08)	(0.18)	(0.59)
zln(Banks with Branch)	0.020***	-0.020***	0.002	0.004	-0.002
	(<0.01)	(<0.01)	(0.32)	(0.27)	(0.32)
zln(Bank Lenders)	-0.040***	0.045***	0.002	-0.009	0.001
	(<0.01)	(<0.01)	(0.47)	(0.22)	(0.85)
zln(Nonbank Lenders)	0.042***	-0.045***	0.001	-0.004	0.004
	(<0.01)	(<0.01)	(0.68)	(0.48)	(0.14)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	2986	2986	2986	2986	2986
R^2	0.211	0.079	0.014	0.010	0.012
$\overline{\Delta Share^{LenderClass}_{county}}$	-0.010	0.053	0.037	-0.037	0.015

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Cross-Sectional Heterogeneity in Response to the Big4 Retreat: Combined
This table presents OLS estimates from the regressions of changes in the county-level share of mortgage originations for lender classes from 2009-2013 on the county-level change in Big4 share of originations during this time period. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). The dependent variables are the respective county-level change in share from 2009-2013 for each lender class (so each county will have observations for each nonBig4 lender class) in columns (1-2). In column (3) the dependent variables is the lender-class share change only now independently standardized to mean zero and unit variance for each lender class. $\Delta Share^{Big4}_{county}$ represents the change for the Big4. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. There is no overall intercept in these regressions so that each lender class indicator represents the respective average change in share for that class over the sample period. Standard errors are clustered by MSA.

	(1) $\Delta Share^{LenderClass}_{county}$	(2) $\Delta Share^{LenderClass}_{county}$	(3) $z\Delta Share^{LenderClass}_{county}$
$\mathbb{1}$(Small Banks)	-0.010***	-0.009***	
	(<0.01)	(<0.01)	
$\mathbb{1}$(Shadow Banks)	0.053***	0.053***	
	(<0.01)	(<0.01)	
$\mathbb{1}$(Fintech)	0.038***	0.038***	
	(<0.01)	(<0.01)	
$\mathbb{1}$(Large Banks)	-0.037***	-0.035***	
	(<0.01)	(<0.01)	
$\mathbb{1}$(Credit Unions)	0.015***	0.017***	
	(<0.01)	(<0.01)	
$\mathbb{1}$(Small Banks) $\times z\Delta Share^{Big4}_{county}$		-0.046***	-0.420***
		(<0.01)	(<0.01)
$\mathbb{1}$(Shadow Banks) $\times z\Delta Share^{Big4}_{county}$		-0.016***	-0.185***
		(<0.01)	(<0.01)
$\mathbb{1}$(Fintech) $\times z\Delta Share^{Big4}_{county}$		-0.003**	-0.105***
		(0.01)	(<0.01)
$\mathbb{1}$(Large Banks) $\times z\Delta Share^{Big4}_{county}$		-0.003*	-0.048
		(0.09)	(0.12)
$\mathbb{1}$(Credit Unions) $\times z\Delta Share^{Big4}_{county}$		-0.003***	-0.072***
		(0.02)	(0.02)
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	14930	14930	14930
R^2	0.190	0.262	0.048

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Cross-Sectional Heterogeneity in Response to the Big4 Retreat: IV
This table presents IV estimates from the regressions of changes in the county-level share of mortgage originations for each lender class from 2009-2013 on the county-level change in Big4 share of originations during this time period. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). The dependent variables are the respective county-level change in share from 2009-2013 for each lender class, and $\Delta Share^{Big4}_{county}$ represents the change for the Big4, which is instrumented in these regressions with the 2009 county-level share of the Big4. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. $\overline{\Delta Share}^{LenderClass}_{county}$ represents the mean of the dependent variable. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

	(1) Small Banks	(2) Shadow Banks	(3) Fintech	(4) Large Banks	(5) Credit Unions
$z\Delta \widehat{Share}^{Big4}_{county}$	-0.050***	-0.013***	-0.007***	0.001	-0.002
	(<0.01)	(<0.01)	(<0.01)	(0.59)	(0.45)
zln(Population)	-0.015*	0.017**	-0.001	0.002	-0.003
	(0.06)	(0.01)	(0.54)	(0.61)	(0.41)
zMinority	0.002	-0.005	0.002	-0.004	0.003
	(0.72)	(0.29)	(0.11)	(0.15)	(0.16)
zIncome	0.001	0.002	-0.003**	0.003	-0.002
	(0.86)	(0.66)	(0.04)	(0.24)	(0.37)
zSubprime	-0.015**	0.010**	-0.001	0.008***	-0.000
	(0.02)	(0.04)	(0.41)	(0.01)	(0.82)
zHHI	0.005	-0.009**	0.003**	0.003	-0.001
	(0.21)	(0.01)	(0.05)	(0.20)	(0.52)
zln(Banks with Branch)	0.020***	-0.021***	0.002	0.004	-0.003
	(<0.01)	(<0.01)	(0.21)	(0.29)	(0.28)
zln(Bank Lenders)	-0.040***	0.045***	0.003	-0.009	0.001
	(<0.01)	(<0.01)	(0.33)	(0.21)	(0.89)
zln(Nonbank Lenders)	0.042***	-0.046***	0.001	-0.004	0.004
	(<0.01)	(<0.01)	(0.59)	(0.47)	(0.17)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	2986	2986	2986	2986	2986
R^2	0.210	0.077	-0.016	0.010	0.010
Fstat	537	537	537	537	537

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: IV: Loan Growth by Lender Class

This table presents IV estimates from the regressions of changes in county-level growth in mortgage originations for each lender class from 2009-2013 on the county-level loan growth for Big4 lenders during this time period. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between $10 billion and $1 trillion in 2011, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). The dependent variables are the respective county-level loan growth from 2009-2013 for each lender class, and $Growth^{Big4}_{county}$ represents the change for the Big4, which is instrumented in these regressions with the 2009 county-level share of the Big4. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. $\overline{Growth}^{LenderClass}_{county}$ represents the mean of the dependent variable. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

	(1) Small Banks	(2) Shadow Banks	(3) Fintech	(4) Large Banks	(5) Credit Unions
$z\,\widehat{Growth}^{Big4}_{county}$	-0.093***	-0.029***	-0.012***	-0.007**	-0.007***
	(<0.01)	(<0.01)	(<0.01)	(0.04)	(0.01)
zln(Population)	0.016	0.030***	0.003	0.009*	-0.002
	(0.32)	(<0.01)	(0.27)	(0.08)	(0.53)
zMinority	0.009	0.002	0.003**	-0.001	0.006**
	(0.40)	(0.71)	(0.03)	(0.72)	(0.02)
zIncome	-0.002	-0.003	-0.004**	0.001	-0.003
	(0.86)	(0.51)	(0.03)	(0.81)	(0.12)
zSubprime	-0.021**	0.006	-0.003	0.005	-0.001
	(0.04)	(0.37)	(0.13)	(0.15)	(0.69)
zHHI	0.009	-0.004	0.004***	0.006**	0.001
	(0.12)	(0.41)	(0.01)	(0.05)	(0.55)
zln(Banks with Branch)	0.031**	-0.013**	0.005**	0.008**	0.001
	(0.03)	(0.04)	(0.04)	(0.04)	(0.76)
zln(Bank Lenders)	-0.098***	0.016	-0.005	-0.019**	-0.008
	(<0.01)	(0.27)	(0.21)	(0.02)	(0.30)
zln(Nonbank Lenders)	0.025	-0.045***	-0.001	-0.008	0.005
	(0.17)	(<0.01)	(0.74)	(0.13)	(0.30)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	2986	2986	2986	2986	2986
Fstat	500.471	500.471	500.471	500.471	500.471

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Within-Lender Reallocation

This table presents OLS estimates from the regressions of changes in the log of individual lender-county mortgage originations from 2009-2013 on the county-level change in Big4 share of originations during this time period where the lender has at least 10 originations in the county in either 2009 or 2013. *Big4* represents Bank of America (*BoA*), Citi, JP Morgan, and Wells Fargo, *Large Banks* includes banks with assets between \$10 billion and \$1 trillion in 2011, *Small Banks* includes banks with assets less than \$10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $\Delta Share^{Big4}_{county}$ and $\Delta Share^{BoA}_{county}$ respectively represents the change for the Big4 and BoA. For the IV regressions, these variables are instrumented with their respective 2009 county-level share of mortgage originations. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. All specifications include individual lender and county fixed effects. Standard errors are clustered by county and lender.

	(1) OLS	(2) IV	(3) OLS	(4) IV
$\mathbb{1}$(Small Banks) × $z\Delta Share^{Big4}_{county}$	-0.279***	-0.326***		
	(<0.01)	(<0.01)		
$\mathbb{1}$(Shadow Banks) × $z\Delta Share^{Big4}_{county}$	-0.274***	-0.145*		
	(<0.01)	(0.07)		
$\mathbb{1}$(Fintech) × $z\Delta Share^{Big4}_{county}$	-0.237***	-0.044		
	(<0.01)	(0.43)		
$\mathbb{1}$(Large Banks) × $z\Delta Share^{Big4}_{county}$	-0.172***	-0.120		
	(<0.01)	(0.11)		
$\mathbb{1}$(Credit Unions) × $z\Delta Share^{Big4}_{county}$	-0.148***	-0.017		
	(<0.01)	(0.83)		
$\mathbb{1}$(Small Banks) × $z\Delta Share^{BoA}_{county}$			-0.195***	-0.167***
			(<0.01)	(<0.01)
$\mathbb{1}$(Shadow Banks) × $z\Delta Share^{BoA}_{county}$			-0.116***	-0.046
			(<0.01)	(0.29)
$\mathbb{1}$(Fintech) × $z\Delta Share^{BoA}_{county}$			-0.044	0.031
			(0.38)	(0.44)
$\mathbb{1}$(Large Banks) × $z\Delta Share^{BoA}_{county}$			-0.088***	-0.051
			(0.01)	(0.20)
$\mathbb{1}$(Credit Unions) × $z\Delta Share^{BoA}_{county}$			-0.021	0.049
			(0.51)	(0.18)
Individual Lender FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	62505	62505	62505	62505
R^2	0.007	0.004	0.003	0.002
F-stat		162.875		1360.371

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Credit Demand Side: Borrower Preference for Banks

This table presents 2SLS estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the county-level change in Big4 share of originations during this time period and its interaction with consumers' historical preference for borrowing from a bank over a nonbank. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than \$10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $\Delta Share^{Big4}_{county}$ represents the change in county-level share of mortgage origination for Big4 lenders from 2009 to 2013, *PreferBanks* is the average difference in origination conversion rates for banks minus origination conversion rates for nonbank from 2001-2009 (see Section 5.1), and *HiPreferBanks* is an indicator variable equal to one for counties with above-median *PreferBanks*. The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

	Small Banks			Shadow Banks			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z$\Delta Share^{Big4}_{county}$	-0.043***	-0.040***	-0.030***	-0.018***	-0.018***	-0.019***	-0.006***	-0.007***	-0.007***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zPreferBanks	-0.020***	-0.017***		0.017***	0.015***		-0.005***	-0.005***	
	(<0.01)	(<0.01)		(<0.01)	(<0.01)		(<0.01)	(<0.01)	
z$\Delta Share^{Big4}_{county}$×zPreferBanks	-0.010*	-0.013**		0.004	0.004		-0.000	-0.000	
	(0.06)	(0.03)		(0.27)	(0.36)		(0.73)	(0.96)	
HiPreferBanks			-0.019***			0.015**			-0.005**
			(<0.01)			(0.02)			(0.02)
z$\Delta Share^{Big4}_{county}$×HiPreferBanks			-0.030**			0.007			0.000
			(0.03)			(0.45)			(0.92)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3033	2972	2972	3033	2972	2972	3033	2972	2972
R^2	0.214	0.238	0.230	0.074	0.100	0.089	0.007	0.007	-0.006
Fstat	128.602	121.376	82.227	128.602	121.376	82.227	128.602	121.376	82.227

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Credit Supply Side: Securitizability of Loans

This table presents 2SLS estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the county-level change in Big4 share of originations during this time period and its interaction with the share of loans through government-supported loan programs. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than $10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $\Delta Share^{Big4}_{county}$ represents the change in county-level share of mortgage origination for Big4 lenders from 2009 to 2013, *GSLP* is the average share of loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac from 2001-2009, and *HiGSLP* is an indicator variable equal to one for counties with above-median GSLP. The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

	Small Banks			Shadow Banks			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z$\Delta Share^{Big4}_{county}$	-0.048***	-0.046***	-0.061***	-0.011***	-0.013***	-0.004	-0.008***	-0.007***	-0.007***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.44)	(<0.01)	(<0.01)	(<0.01)
zGSLP	0.020***	0.014***		-0.005	-0.000		0.001	0.001	
	(<0.01)	(<0.01)		(0.16)	(0.90)		(0.34)	(0.39)	
z$\Delta Share^{Big4}_{county}$×zGSLP	0.008***	0.007**		-0.007**	-0.005		0.000	0.000	
	(0.01)	(0.03)		(0.04)	(0.13)		(0.83)	(0.92)	
HiGSLP			0.014**			0.003			0.002
			(0.01)			(0.39)			(0.22)
z$\Delta Share^{Big4}_{county}$×HiGSLP			0.022**			-0.015			0.000
			(0.03)			(0.13)			(0.86)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3050	2985	2985	3050	2985	2985	3050	2985	2985
R^2	0.203	0.223	0.216	0.033	0.074	0.069	-0.023	-0.011	-0.011
Fstat	156.601	229.675	93.068	156.601	229.675	93.068	156.601	229.675	93.068

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Horse Race: Independent Contributions of Supply and Demand Factors
This table presents 2SLS estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the county-level change in Big4 share of originations during this time period and its interaction with the share of loans through government-supported loan programs and its interaction with consumers' historical preference for borrowing from a bank over a nonbank. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than \$10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $\Delta Share^{Big4}_{county}$ represents the change in county-level share of mortgage origination for Big4 lenders from 2009 to 2013, *GSLP* is the average share of loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac from 2001-2009, *HiGSLP* is an indicator variable equal to one for counties with above-median GSLP, *PreferBanks* is the average difference in origination conversion rates for banks minus origination conversion rates for nonbank from 2001-2009 (see Section 5.1), and *HiPreferBanks* is an indicator variable equal to one for counties with above-median *PreferBanks.* The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

	Small Banks		Shadow Banks		Fintech	
	(1)	(2)	(3)	(4)	(5)	(6)
z$\Delta Share^{Big4}_{county}$	-0.037***	-0.046***	-0.018***	-0.012**	-0.007***	-0.006***
	(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(<0.01)
GSLP	0.017***		-0.002		0.000	
	(<0.01)		(0.69)		(0.86)	
zPreferBanks	-0.023***		0.017***		-0.005***	
	(<0.01)		(<0.01)		(<0.01)	
z$\Delta Share^{Big4}_{county}$×zGSLP	0.007		-0.005		-0.001	
	(0.17)		(0.32)		(0.68)	
z$\Delta Share^{Big4}_{county}$×zPreferBanks	-0.015*		0.005		0.000	
	(0.07)		(0.35)		(1.00)	
HiGSLP		0.030***		-0.005		0.001
		(<0.01)		(0.47)		(0.80)
HiPreferBanks		-0.033***		0.020***		-0.004*
		(<0.01)		(0.01)		(0.07)
z$\Delta Share^{Big4}_{county}$×HiGSLP		0.031***		-0.017*		-0.002
		(<0.01)		(0.07)		(0.36)
z$\Delta Share^{Big4}_{county}$×HiPreferBanks		-0.028***		0.009		-0.000
		(<0.01)		(0.15)		(0.97)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2972	2972	2972	2972	2972	2972
R^2	0.246	0.234	0.097	0.085	0.010	-0.001
Fstat	47.077	55.117	47.077	55.117	47.077	55.117

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Lender Composition and Redistributive Effects

This table presents OLS estimates from the regressions of the log of the size of the approved mortgage loan during 2009-2013 on the county mortgage market share characteristics before and after the passage of Dodd-Frank (Post2011) and various borrower characteristics in the spirit of the tests in D'Acunto and Rossi (2017). The results are computed separately for loans in five size categories as indicated in each column, and are for originated new purchase loans that are owner-occupied and first lien. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than $10 billion in 2011. *Nonbanks* include all non-bank, non-credit union lenders (such as independent mortgage companies) including fintech lenders, *Small/Nonbanks* is the number of loans made by small banks divided by loans made by nonbanks in the county, *Black*, *Asian*, and *Latino* are indicator variables equal to one according to the borrowers race/ethnicity, while those same variables preceded by *Avg-* represents the share of applicats in the county of that respective race/ethnicity, *Income* is the log of applicant income, *HomePrice* is the median county home price for the year, Independent variables that are standardized are indicated by "z" and have a mean of zero and unit variance. Standard errors are clustered by county.

	(1) <100k	(2) 100k-200k	(3) 200k-417k	(4) 417k-700k	(5) >700k
Big4 × Post2011	-0.03	-0.04***	-0.05***	-0.01	0.26***
	(0.15)	(<0.01)	(<0.01)	(0.51)	(<0.01)
zSmall/Nonbanks × Post2011	-0.00	0.00**	-0.00***	0.00	0.01
	(0.80)	(0.01)	(<0.01)	(0.21)	(0.44)
Big4 × Post2011 × zSmall/Nonbanks	0.00	-0.00	0.02***	-0.03	-0.07
	(0.82)	(0.38)	(<0.01)	(0.34)	(0.42)
Big4	0.05**	-0.01	-0.02**	-0.01	-0.09
	(0.01)	(0.55)	(0.03)	(0.71)	(0.30)
zSmall/Nonbanks	-0.01***	-0.00*	0.00**	-0.00	0.04***
	(<0.01)	(0.08)	(0.03)	(0.59)	(<0.01)
Black	0.00	0.01***	-0.00	-0.02***	-0.03***
	(0.31)	(<0.01)	(0.24)	(<0.01)	(<0.01)
Asian	0.02***	0.01***	0.02***	0.00	-0.02***
	(<0.01)	(<0.01)	(<0.01)	(0.27)	(<0.01)
Hispanic	-0.01	-0.01**	-0.02***	-0.02***	-0.02***
	(0.11)	(0.02)	(<0.01)	(<0.01)	(<0.01)
Avg-Black (county)	0.00	-0.03	-0.03	-0.01	0.22
	(1.00)	(0.29)	(0.18)	(0.85)	(0.27)
Avg-Asian (county)	-0.04	-0.06	0.12**	0.04	-0.19
	(0.62)	(0.21)	(0.04)	(0.48)	(0.27)
Avg-Hispanic (county)	-0.06	0.01	-0.10***	0.07	-0.34**
	(0.49)	(0.68)	(0.01)	(0.11)	(0.01)
Income	0.10***	0.15***	0.24***	0.12***	0.31***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
HomePrice	0.01	0.14***	0.13***	0.04***	0.12**
	(0.49)	(<0.01)	(<0.01)	(<0.01)	(0.02)
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	1850037	4471876	3818419	504023	194023
R^2	0.07	0.17	0.33	0.19	0.38

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

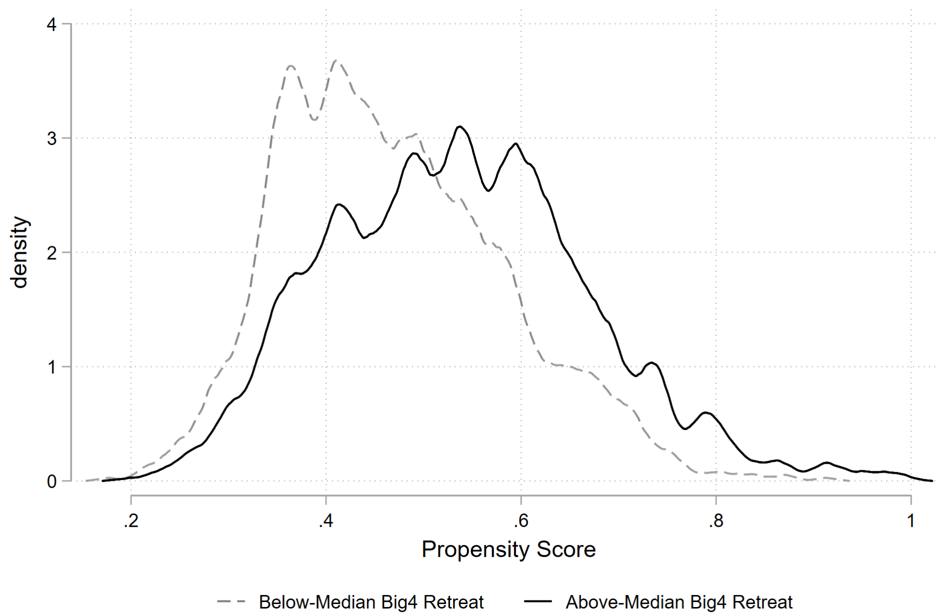
Table 13: Granularity in the Mortgage Market: the Retreat of Bank of America

This table presents OLS and IV estimates from the regressions of changes in the county-level share of mortgage originations for small banks (columns 1-3), shadow banks (columns 4-5) or fintech lenders (columns 6-7) from 2009-2013 on the county-level change in Big4 share of originations during this time period. *BoA* represents Bank of America, *Small Banks* includes banks with assets less than $10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $\Delta Share^{BoA}_{county}$ represents the change in county-level share of mortgage origination for BoA from 2009 to 2013. $Share^{09BoA}_{county}$ represents BoA's the 2009 county-level share of originations, $Share^{07CW}_{county}$ represents Countrywide's the 2007 county-level share of originations, *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. *Fstat* is the F statistic from the first stage regression. Standard errors are clustered by MSA.

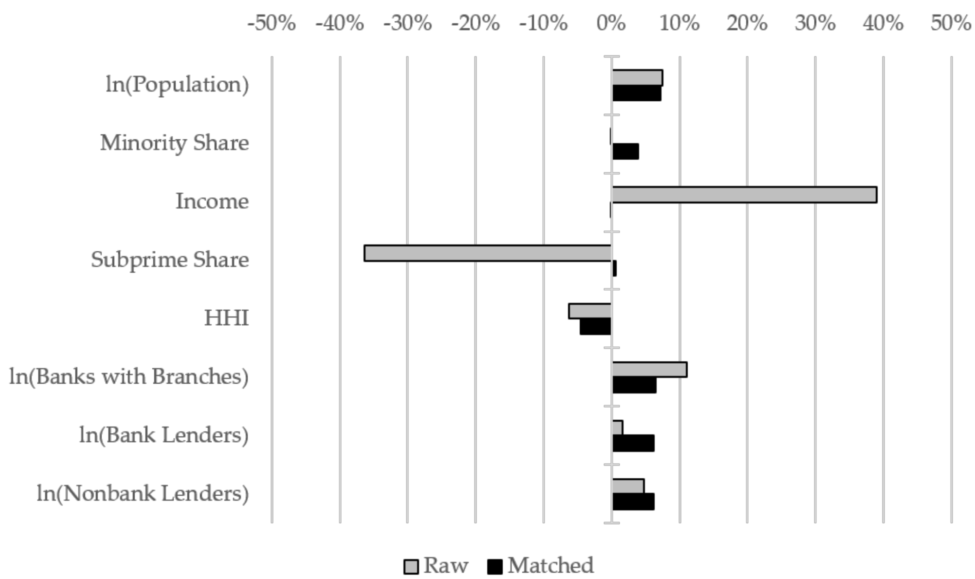
	Small Banks			Shadow Banks		Fintech	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	IV	IV	IV	IV-CW	IV	IV-CW
Instrument		$Share^{09BoA}_{county}$	$Share^{07CW}_{county}$	$Share^{09BoA}_{county}$	$Share^{07CW}_{county}$	$Share^{09BoA}_{county}$	$Share^{07CW}_{county}$
$z\Delta Share^{BoA}_{county}$	-0.025***	-0.021***	-0.032***	-0.009***	-0.012***	-0.003***	-0.004**
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(0.01)
zln(Population)	-0.005	-0.005	-0.004	0.020***	0.020***	0.000	0.000
	(0.59)	(0.54)	(0.67)	(0.01)	(<0.01)	(0.92)	(0.87)
zMinority	0.003	0.003	0.003	-0.005	-0.005	0.002*	0.002*
	(0.58)	(0.56)	(0.62)	(0.34)	(0.33)	(0.06)	(0.08)
zIncome	0.007	0.007	0.006	0.003	0.003	-0.002	-0.002
	(0.13)	(0.10)	(0.18)	(0.42)	(0.47)	(0.17)	(0.14)
zSubprime	-0.017***	-0.017***	-0.016**	0.010*	0.010**	-0.002	-0.002
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.37)	(0.38)
zln(Banks with Branch)	0.014*	0.014*	0.013*	-0.022***	-0.022***	0.001	0.001
	(0.07)	(0.07)	(0.08)	(<0.01)	(<0.01)	(0.44)	(0.46)
zHHI	0.001	0.001	0.000	-0.010***	-0.010***	0.002	0.002
	(0.86)	(0.81)	(0.94)	(<0.01)	(<0.01)	(0.15)	(0.17)
zln(Bank Lenders)	-0.052***	-0.051***	-0.054***	0.041***	0.040***	0.001	0.001
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.72)	(0.77)
zln(Nonbank Lenders)	0.035***	0.036***	0.034***	-0.048***	-0.048***	0.000	0.000
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.89)	(0.94)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2986	2986	2986	2986	2986	2986	2986
R^2	0.083	0.082	0.079	0.052	0.052	0.010	0.006
Fstat		4983.203	85.325	4983.203	85.325	4983.203	85.325

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figures and Tables



(a) Overlap in Propensity Score



(b) Pre- and Post-Matching Balance

Figure A.1: Propensity Score Matching Diagnostics
This figure presents diagnostics for the propensity score matching estimates in Table A.2, where we compare changes in county-level mortgage lending shares by lender classes across counties with above-median (treatment) and below-median (control) 2009-2013 retreat in Big4 lending shares. We match on the following variables (defined in Table A.2): *ln(Population)*, *Minority*, *Income*, *Subprime*, *HHI*, *ln(Banks with Branch)*, *ln(Bank Lenders)*, and *ln(Nonbank Lenders)*. Panel (a) the overlap in propensity scores for the above-median Big4 Retreat counties and their matches. Panel (b) presents the differences in treatment and control county characteristics before matching (gray) and after matching (black) as scaled by the standard deviation of the variables.

Table A.1: Initial Big4 Share and County Characteristics

This table presents the mean [median] county 2009 characteristics according to the county-level Big4 mortgage origination shares in 2009. *Big4* represents Bank of America (*BoA*), Citi, JP Morgan, and Wells Fargo, *Population* is the 2009 population in thousands, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income in thousands, *Subprime* is the 2009 share of the population with FICO below 660, and *HHI* is the 2009 county banking competition base on deposits.

Big4 2009 Share Quintile	Population	Minority	Income	Subprime	HHI
1 (smallest share)	28.98	0.18	29.96	0.34	0.36
	[18.67]	[0.09]	[29.16]	[0.34]	[0.30]
2	56.34	0.19	31.06	0.34	0.30
	[27.7]	[0.11]	[30.25]	[0.34]	[0.25]
3	67.27	0.21	31.87	0.34	0.31
	[26.06]	[0.14]	[30.7]	[0.34]	[0.25]
4	130.79	0.23	34.00	0.32	0.29
	[36.63]	[0.18]	[33.11]	[0.31]	[0.22]
5 (largest share)	205.97	0.25	36.83	0.29	0.31
	[29.16]	[0.19]	[34.52]	[0.27]	[0.23]

Table A.2: Response to the Big4 Retreat: Matching

This table presents estimates of the relative changes in the county-level share of mortgage originations for each lender class from 2009-2013 for counties that experienced above-median Big4 retreat (treated) with below-median Big4 retreat (control) using propensity score matching and then mahalanobis nearest-neighbor matching. Both methodologies use the three nearest neighbors to the treated counties as counterfactuals and compute the average treatment effect on the treated ($ATET$). *Big4 retreat* represents change in the collective share of Bank of America, Citi, JP Morgan, and Wells Fargo during 2009-2013 ($\Delta Share^{Big4}_{county}$). *Large Banks* includes banks with assets between \$10 billion and \$1 trillion in 2011, *Small Banks* includes banks with assets less than \$10 billion in 2011, *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). We match on the following variables: *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. We compute robust standard errors, with bias-adjusted standard errors (Abadie and Imbens, 2011) for the mahalanobis matching where we require the match within state.

	Propensity Score		Mahalanobis	
	$\hat{\beta}^{PS}_{ATET}$	p-value	$\hat{\beta}^{Mahalanobis}_{ATET}$	p-value
Small Banks	0.063***	(0.00)	0.066***	(0.00)
Shadow Banks	0.025***	(0.00)	0.025***	(0.00)
Fintech	0.005***	(0.00)	0.005***	(0.00)
Large Banks	0.009***	(0.00)	0.002	(0.64)
Credit Unions	0.004**	(0.04)	0.002	(0.27)
Within-State	No		Yes	
Treated	1500		1455	
Control	1487		1467	
Total	2987		2922	

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Demand Side: Borrower Preference for Banks – Reduced Form

This table presents reduced form estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the 2009 county-level Big4 share of originations during this time period and its interaction with consumers' historical preference for borrowing from a bank over a nonbank. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than \$10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $Share09^{Big4}_{county}$ represents the county-level share of mortgage origination for Big4 lenders in 2009, *PreferBanks* is the average difference in origination conversion rates for banks minus origination conversion rates for nonbank from 2001-2009 (see Section 5.1), and *HiPreferBanks* is an indicator variable equal to one for counties with above-median *PreferBanks*.The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by MSA.

	Small Banks			Shadow Banks			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z$Share09^{Big4}_{county}$	0.034***	0.034***	0.030***	0.013***	0.014***	0.015***	0.005***	0.005***	0.006***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
zPreferBanks	-0.014***	-0.014***		0.020***	0.017***		-0.003***	-0.004***	
	(<0.01)	(<0.01)		(<0.01)	(<0.01)		(<0.01)	(<0.01)	
z$Share09^{Big4}_{county}$×zPreferBanks	0.009***	0.010***		-0.002	-0.002		0.001	0.000	
	(0.01)	(0.01)		(0.42)	(0.46)		(0.44)	(0.79)	
HiPreferBanks			-0.017***			0.018***			-0.004**
			(0.01)			(0.01)			(0.04)
z$Share09^{Big4}_{county}$×HiPreferBanks			0.016***			-0.005			0.000
			(<0.01)			(0.15)			(0.90)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3033	2972	2972	3033	2972	2972	3033	2972	2972
R^2	0.287	0.303	0.299	0.252	0.277	0.269	0.283	0.287	0.282

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Supply Side: Securitizability of Loans – Reduced Form

This table presents reduced form estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the 2009 county-level Big4 share of originations during this time period and its interaction with the share of loans through government-supported loan programs. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than $10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $Share09^{Big4}_{county}$ represents the county-level share of mortgage origination for Big4 lenders in 2009, *GSLP* is the average share of loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac from 2001-2009, and *HiGSLP* is an indicator variable equal to one for counties with above-median GSLP. The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by MSA.

	Small Banks			Shadow Banks			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z$Share09^{Big4}_{county}$	0.038***	0.039***	0.052***	0.008***	0.010***	0.006*	0.006***	0.006***	0.006***
	(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(0.07)	(<0.01)	(<0.01)	(<0.01)
zGSLP	0.015***	0.012***		-0.006*	-0.001		0.000	0.001	
	(<0.01)	(<0.01)		(0.09)	(0.76)		(0.77)	(0.57)	
z$Share09^{Big4}_{county}$×zGSLP	-0.007***	-0.007***		0.005*	0.004		-0.000	-0.000	
	(<0.01)	(<0.01)		(0.05)	(0.19)		(0.69)	(0.61)	
HiGSLP			0.015***			-0.000			0.002
			(0.01)			(0.97)			(0.39)
z$Share09^{Big4}_{county}$×HiGSLP			-0.021***			0.007*			0.000
			(<0.01)			(0.08)			(0.75)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3050	2985	2985	3050	2985	2985	3050	2985	2985
R^2	0.291	0.303	0.302	0.230	0.263	0.263	0.277	0.279	0.279

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Horse Race – Reduced Form

This table presents reduced form estimates from the regressions of changes in the county-level share of mortgage originations for small banks, shadow banks, or fintech lenders from 2009-2013 on the county-level change in Big4 share of originations during this time period and its interaction with the share of loans through government-supported loan programs and its interaction with consumers' historical preference for borrowing from a bank over a nonbank. *Big4* represents Bank of America, Citi, JP Morgan, and Wells Fargo, *Small Banks* includes banks with assets less than $10 billion in 2011. *Shadow Banks* include all non-bank, non-credit union, non-fintech lenders (such as independent mortgage companies), *Fintech* includes nonbanks with a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender (Buchak et al., 2018a). $Share09^{Big4}_{county}$ represents the change in county-level share of mortgage origination for Big4 lenders from 2009 to 2013, *GSLP* is the average share of loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, or Farmer Mac from 2001-2009, *HiGSLP* is an indicator variable equal to one for counties with above-median GSLP, *PreferBanks* is the average difference in origination conversion rates for banks minus origination conversion rates for nonbank from 2001-2009 (see Section 5.1), and *HiPreferBanks* is an indicator variable equal to one for counties with above-median *PreferBanks*. The dependent variables are the county-level change in share from 2009-2013 for each lender class. The following control variables are included where indicated at the bottom of the table, but not shown to save space. *ln(Population)* is the log of the 2009 population, *Minority* is the 2009 nonwhite share of the population, *Income* is the 2009 per capita income, *Subprime* is the 2009 share of the population with FICO below 660, *HHI* is the 2009 county banking competition base on deposits, *ln(Banks with Branch)* is the log of the number of banks with a physical branch in the county in 2009, *ln(Bank Lenders)* is the log of the number of banks with at least one mortgage loan in the county in 2009, and *ln(Nonbank Lenders)* is the log of the number of shadow banks or fintech lenders with at least one mortgage loan in the county in 2009. All continuous independent variables are standardized as indicated by "z" to have a mean of zero and unit variance. Standard errors are clustered by MSA.

	Small Banks		Shadow Banks		Fintech	
	(1)	(2)	(3)	(4)	(5)	(6)
z$Share09^{Big4}_{county}$	0.033***	0.042***	0.013***	0.010***	0.005***	0.005***
	(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(<0.01)
zGSLP	0.011**		0.000		0.000	
	(0.01)		(0.97)		(0.89)	
zPreferBanks	-0.012***		0.017***		-0.004***	
	(0.01)		(<0.01)		(<0.01)	
z$Share09^{Big4}_{county}$×zGSLP	-0.005**		0.002		0.000	
	(0.03)		(0.43)		(0.99)	
z$Share09^{Big4}_{county}$×zPreferBanks	0.008**		-0.002		0.000	
	(0.02)		(0.52)		(0.80)	
HiGSLP		0.015**		0.001		0.001
		(0.01)		(0.84)		(0.55)
HiPreferBanks		-0.015**		0.018***		-0.004*
		(0.01)		(0.01)		(0.05)
z$Share09^{Big4}_{county}$×HiGSLP		-0.019***		0.007		0.000
		(<0.01)		(0.13)		(0.70)
z$Share09^{Big4}_{county}$×HiPreferBanks		0.014***		-0.004		0.000
		(<0.01)		(0.25)		(0.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2972	2972	2972	2972	2972	2972
R^2	0.309	0.307	0.278	0.270	0.287	0.283

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$