Government-Sponsored Wholesale Funding and the Industrial Organization of Bank Lending[*]

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Abstract

Several wholesale funding markets are dominated by government agencies such as the Federal Home Loan Bank (FHLB), which collectively channel hundreds of billions of dollars into the banking sector every year. Proponents of this intervention argue that it lowers retail borrowing costs significantly. This paper exploits quasi-experimental variation in access to low-cost wholesale funding from the FHLB arising from banks mergers, and shows that access to this funding source is associated with an 18-basis-point reduction in a bank's mortgage rates and a 16.3% increase in mortgage lending. This effect is 25% stronger for small community banks. At the market level, a census tract experiences an increase in local competition after a local bank joins the FHLB, with the market concentration index (HHI) falling by 1.5 percentage points. This intensified local competition pushes other lenders to lower their mortgage rates by 7.4 basis points, and overall market lending grows by 5%. Estimates of a structural model of the US mortgage market imply that the FHLB increases annual mortgage lending in the US by $50 billion, and saves borrowers $4.7 billion in interest payments every year, mainly through changing the competitive landscape of the mortgage market.

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1   Introduction

Banks in the US currently rely heavily on wholesale funding to resolve the mismatch between their deposits and their lending. In fact, more than 25% of banks' total liabilities came from wholesale funding sources during the period 2002–2018.[1] In the wholesale funding market, many government agencies are intensively involved to help support mortgage lending, agriculture-related lending, and credit for other areas of the economy. In 2018, for example, the government-sponsored Federal Home Loan Banks provided $729 billion of mortgage collateralized wholesale funding to mortgage lenders, accounting for 65% of all mortgage collateralized wholesale lending.[2] Despite the central role of government-sponsored wholesale funding, the effects of this support on lending markets are not fully understood. On the one hand, the extension of credit by government-sponsored wholesale funding facilities to banks of all sizes could increase market efficiency by reducing large banks' market power, but on the other hand, government intervention could encourage excessive risk taking (Stojanovic, Vaughan, and Yeager, 2008) and destabilizing liquidity transformation (Sundaresan and Xiao, 2018). This ambiguity has led to fierce debates, and has caused contradictory shifts in policy in regards to extending public wholesale funding to non-depository lenders, which have grown dramatically in many lending markets.[3]

To fill in this knowledge gap, this paper (1) empirically evaluates the impact of government-sponsored wholesale funding on mortgage lending, mortgage interest rates, and local bank concentration, and (2) builds and estimates a quantitative model of local bank lending systems to explore how access to government-sponsored credit shapes the structure, efficiency, and performance of bank lending markets.

The empirical analysis focuses on a specific government-sponsored enterprise—Federal Home Loan Banks (FHLB), whose primary business is to provide collateralized funding (FHLB advances) exclusively to their member banks to support their mortgage lending.[4] The funding cost is close to the risk free rate, and is kept the same for all member banks regardless of their size. The exclusiveness of member funding provides a natural laboratory to evaluate this public funding facility.

The empirical challenge in estimating the impact of access to government-sponsored wholesale

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[1]According to Federal Deposit Insurance Corporation (FDIC), wholesale funds include brokered deposits, public funds, federal funds purchased, FHLB advances, correspondent line of credit advances, and other borrowings. After 2002, the historical average share of wholesale funding in all banks' liabilities is 25.95%, according to Federal Reserve call reports.

[2]The other primary source of mortgage origination funding is through warehouse lending. According the Mortgage Bankers Association, the outstanding warehouse lending was $392B in 2018. Source: MBA's Warehouse Lending Survey.

[3]Buchak, Matvos, Piskorski, and Seru (2018a) and Buchak, Matvos, Piskorski, and Seru (2018b) document that shadow banks' market share in mortgage lending has dramatically increased in the recent years.

[4]There are 11 regional FHLBs, locating across the country. Each Federal Home Loan Bank is a government-sponsored enterprise, federally chartered, but mutually owned by its member institutions. Commercial banks, thrifts, credit unions, community development financial institutions, as well as insurance companies could apply to the FHLB that serves the state where their home office is located.

funding through FHLB membership is that the FHLB application decision is endogenous to the banks' economic conditions. Banks that are on an expanding trajectory tend to apply for FHLB membership to secure more funding sources, and a naïve event study would produce a biased estimate of the effect of accessing FHLB funding. To solve this endogeneity problem, I take a novel approach and explore the exogenous changes in access to FHLB funding that arise from bank mergers. If an FHLB member bank acquires a non-FHLB member target, the branches of the target bank will operate under the acquiring bank and automatically get access to FHLB advances after the merger. However the change of target bank branches mixes two effects: a merger effect (managerial change and access to funding sources other than the FHLB) and an FHLB effect. To achieve identification, I further consider multiple-target mergers, where the acquiring bank simultaneously acquires multiple target banks, and the target banks differ in their FHLB membership status. I rely on within-merger comparisons between target bank branches that have access to FHLB advances prior to the merger and those that do not, to difference out the merger effect. The identification assumption is that the target banks in multiple-target mergers share comparable trends regardless of their FHLB membership.

With the multiple-target merger identification strategy, I start my empirical analysis by examining the effect of public external funding access to the recipient banks themselves. The difference-in-differences estimates show that the treated banks reduce their mortgage interest rates by 18 basis points and increase origination by 16.3% after gaining access to external funding through the FHLB. This effect persists for at least 5 years. Compositionally, I find that banks issue mortgages with very similar credit score and loan-to-value (LTV) ratio profiles throughout the period, contrary to the view that public funding encourages banks' risk taking. The only striking change is that the treated banks increase their fixed-rate mortgage positions by 5% due to the structural feature of FHLB funding. Furthermore, I find that small community banks react 5% more strongly to this external source of funding, consistent with the well-documented fact that small banks have more funding challenges (Kroszner, 2016; Jacewitz and Pogach, 2018).

I then investigate the effect on the industrial organization of the local mortgage market after extending FHLB funding to the treated local banks. The results show that market competition in the local census tract improves significantly. The market concentration index (HHI) drops by 1.5 percentage points, from a baseline of 15%. The intensified local competition affects several market outcomes. First, competing lenders reduce their mortgage rates by 7.4 basis points following the treated banks' 18-basis-point reduction. As a result, the market-level interest rate falls by 8 basis points. Second, the local market experiences a growth in mortgage lending of 5%. A closer investigation suggests that roughly two-thirds of the mortgage growth comes from the treated banks, and the remaining third is from their competitors, through a competition channel. Finally, mortgage interest rates become more

responsive to local economic conditions. I find that small (community or regional) banks actively price the local economic risk into their mortgage rates, while the national banks apply a uniform pricing strategy. After small banks gain more market share due to FHLB funding access, they incorporate their superior knowledge of local economic conditions into more mortgages' pricing.

Overall, this evidence suggests that government-sponsored wholesale funding has a substantial positive effect on both individual banks and the local lending market. But this inference is restricted to my multiple-target merger sample for identification purposes, and the shock to the local market is relatively small—one lender gaining access to FHLB funding. It remains unclear how government-sponsored wholesale funding affects banks out of my sample (i.e., national banks), and more importantly, how it affects bank lending through changing the industrial organization beyond simply reducing the funding cost. To tackle this question, I develop and estimate an equilibrium model of the mortgage market to uncover the cost heterogeneity for all banks, with which I am able to quantify the effect of FHLB funding to the full range of banks, as well as the market structure and outcomes. I then carry out a counterfactual exercise to decompose the FHLB effect, and isolate the impact of the reduction in market concentration. I address these questions and concerns by employing a structural strategy.

In my quantitative model, heterogeneous borrowers choose mortgages among different lenders who offer different interest rates and service quality. To capture the realistic borrower substitution pattern for demand, the model allows both observed and unobserved heterogeneity among borrowers following Berry, Levinsohn, and Pakes (1995).[5] On the supply side, banks offer differentiated mortgage products and set optimal interest rates to maximize their profit. If a bank is exposed to funding shocks (e.g. deposit withdraws), temporarily pushing up its marginal cost, the FHLB can serve as a stable alternative funding source for its member banks. Banks of different sizes (national, regional and community) have different cost parameters, and different pricing flexibility to react to local economic conditions.

I estimate the demand and supply parameters separately. On the demand side, two types of instruments are used to alleviate price endogeneity. First, I exploit the fact that the national banks apply a uniform pricing strategy across different regions and use the large banks' national mortgage rates to instrument for their mortgage rates in different markets.[6] Second, I use other lenders' product characteristics (LTVs and proportion of fixed rate mortgage), which would affect the lender's price but

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[5]Similar structural techniques have been recently applied to study markets of different financial products, including mortgages (Buchak et al., 2018a,b; Benetton, 2018), deposits (Egan, Hortaçsu, and Matvos, 2017), insurance (Koijen and Yogo, 2016), corporate lending (Crawford, Pavanini, and Schivardi, 2018) and pensions (Hastings, Hortaçsu, and Syverson, 2017).

[6]The national banks' uniform pricing behavior echoes similar "puzzles" for GSE mortgages (Hurst, Keys, Seru, and Vavra, 2016), grocery products (DellaVigna and Gentzkow, 2018), rental cars (Cho and Rust, 2010), and movie tickets (Orbach and Einav, 2007).

are not correlated with local demand, following Berry et al. (1995). In estimating supply parameters, I leverage the well-identified FHLB effect on mortgage rates in my reduced form exercise to discipline my model, and identify the cost parameters for different banks and the effective cost of FHLB advances. My model effectively captures the mortgage rate distribution and the FHLB effect on different groups of banks illustrated in my reduced form analysis.

With this quantitative model, I consider two counterfactuals to fully characterize the effect of public funding facilities. First, I simulate an economy without the FHLB. Market concentration (HHI) increases by 2.4 percentage points, average mortgage rates rise by 11 basis points, aggregate mortgage lending shrinks by 7%, and the borrowers experience welfare loss of 10.3%. Such a large impact is due to the two roles that the FHLB plays in addressing market imperfections: shielding banks from liquidity shocks (the direct effect) and providing equal external funding access (the competition effect). Since the direct effect could also be achieved by the private market (e.g., warehouse lending), the competition effect is more informative for the value of public provision of wholesale funding.

To isolate the competition effect of the FHLB, I consider a second counterfactual where the FHLB still exists, but chooses to offer different advance prices to different banks. The advance prices are made so that the average funding cost of FHLB member banks is the same as in the current equilibrium, but the market structure is the same as in the first counterfactual (with no FHLB). Therefore, this counterfactual has the same direct effect as in the current equilibrium. The only difference is the market structure in the mortgage lending, so this exercise would capture the effect of government-sponsored wholesale funding due to the shift of the industrial organization of the lending market (the competition effect). The simulation shows that if the FHLB were to apply this price schedule, aggregate mortgage origination would drop by 2.46%, banks' markup would rise by 3 basis points, and borrowers' welfare would drop by 3.76%. A simple back-of-the-envelope calculation implies that the FHLB's impact on the industrial organization of the mortgage market increases mortgage lending by $50 billion and saves borrowers $4.7 billion in interest payments every year.

Literature review. This paper contributes to four main lines of research. First, this paper contributes to the literature that evaluates government intervention in the credit market. There has been extensive study of government guarantee programs, which finds that the Fannie Mae and Freddie Mac mortgage guarantee distorts the banks' incentive (Frame and Wall, 2002) and the housing market (Elenev, Landvoigt, and Van Nieuwerburgh, 2016; Jeske, Krueger, and Mitman, 2013). Similar results are also found for the Small Business Administration guarantee program (Craig, Jackson, and Thomson, 2008; Cowling and Mitchell, 2003). This paper complements this literature by investigating another form of government intervention in the primary lending market.

Second, my paper contributes to the bank lending channel literature, which emphasizes the role

of banks' financial constraints on their credit supply. Campello (2002), Gan (2007), Paravisini (2008) and Gilje, Loutskina, and Strahan (2016), have shown banks are generally financially constrained, and external funding has a positive effect on their lending. This paper further illustrates that the financial frictions are heterogeneous among banks of different sizes (Kashyap and Stein, 2000; Williams, 2017; Kroszner, 2016), which is a potential source of market power. The empirical analysis suggests that public provision of external funding could reduce the uneven distribution of banks' funding cost and intensify the competition of bank lending, which would increase the pass-through of shocks in aggregate credit supply (Scharfstein and Sunderam, 2016; Wang, Whited, Wu, and Xiao, 2018).[7]

Third, this paper adds to the literature on the role of the FHLB in the economy. Bennett, Vaughan, and Yeager (2005), Stojanovic et al. (2008) and Frame, Hancock, and Passmore (2007) study how the FHLB affects the member banks' risk taking and portfolio composition, and find mixed results. Ashcraft, Bech, and Frame (2010) highlights the FHLB's role as a liquidity backstop in the 2008 financial crisis. Sundaresan and Xiao (2018) and Narajabad and Gissler (2018) investigate how the FHLB interacts with the Basel III liquidity requirements and the recent money market reform, and find that FHLB advances are extracted for compliance purposes and unintentionally create potential liquidity fragility. This paper emphasizes the FHLB's unique role in providing equal funding access to banks of different sizes, and improving bank lending through reducing market concentration.

Finally, extensive research argues that small banks have a unique role in the economy by providing soft information and relationship banking. Their low cost of soft information communication (Liberti and Mian, 2009; Levine, Lin, Peng, and Xie, 2019) give them a comparative advantage in small business lending (Berger, Saunders, Scalise, and Udell, 1998; Canales and Nanda, 2012; Berger, Bouwman, and Kim, 2017), where relationship banking is key to overcoming information frictions (Petersen and Rajan, 1994; Berger and Udell, 1995; Cole, 1998; Elsas and Krahnen, 1998; Harhoff and Körting, 1998; Kysucky and Norden, 2015). This paper finds that small banks are also important due to their organizational flexibility to react to economic conditions and set risk-adjusted prices. Thus, this paper provides a novel source of small banks' comparative advantage beyond their low cost of soft information communication.

Overview. The paper proceeds as follows. Section 2 discusses the data and the institutional setting for the FHLB. Section 3 outlines the empirical strategy and describes the characteristics of the sample banks. Section 4 illustrates public funding access's effect on individual banks' mortgage lending, and section 5 demonstrates the effect on market structure and outcomes. Section 6 tests

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[7]An extensive literature also shows the industrial organization of banking has an profound influence on bank lending quality (Liebersohn, 2017), credit access and price (Rice and Strahan, 2010), economic growth (Jayaratne and Strahan, 1996), entrepreneurship (Black and Strahan, 2002; Kerr and Nanda, 2009) and income equality (Beck, Levine, and Levkov, 2010).

the robustness of the reduced form results. In section 7, I develop a model of mortgage lending, and section 8 estimates it. In section 9, I carry out two counterfactual exercises to quantify the effects of the FHLB in a general equilibrium setting. Section 10 concludes.

2 Institutional Setting and Data Description

The institutional details of the Federal Home Loan Bank are important in understanding why this source of government-sponsored wholesale funding would be expected to affect both the recipient banks and the local credit markets more broadly. In this section, I discuss the institutional details about the FHLB, and the data that I use for the empirical analysis.

2.1 Federal Home Loan Banks

The Federal Home Loan Bank system was chartered by Congress in 1932, as a government-sponsored enterprise (GSE) to support mortgage lending and related community investment. It is composed of 11 regional Federal Home Loan Banks[8], which are collectively owned by more than 7,300 member financial institutions. Equity in the FHLB is held by these members and is not publicly traded. Institutions must purchase stock in order to become a member, and in return, members obtain access to low-cost funding (FHLB advances) and also receive dividends based on their stock ownership.

Initially, the FHLB only accepted members from savings and loan associations and insurance companies, and provided funding support to these members. But after the savings and loan crisis of the 1980s, the FHLB system was dramatically reformed by the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989, and opened membership to all federally insured depository institutions, including commercial banks and credit unions. As shown in Figure B1, 90% of all FDIC insured banks have joined the FHLB as of 2017.

As an FHLB member, the primary benefit is to have access to long- and short-term advances (collaterized lending). Advances are primarily collateralized by residential mortgage loans, and government and agency securities.[9] The interest rates of advances are at the level of the treasury rates with comparable maturity plus a very tiny margin. Figure B2 illustrates the historical advance rates of various maturities from an FHLB (Des Moines), and they follow the benchmark rate closely. More importantly, the FHLB is mandated to give the best price daily to all members, regardless of their size or business model. Therefore, the access to such a low-cost funding source is disproportionally

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[8]The regional FHLBs are located in: Atlanta, Boston, Chicago, Cincinnati, Dallas, Des Moines, Indianapolis, New York, Pittsburgh, San Francisco, and Topeka. Historically, there was another regional Federal Home Loan Bank in Seattle, which was merged into Federal Home Loan of Des Moines in 2015. District details can be found at https://www.fhfa.gov/SupervisionRegulation/FederalHomeLoanBanks/Pages/FHLBank-Districts.aspx.

[9]Community financial institutions may pledge small business, small farm, and small agri-business loans as collateral for advances.

more beneficial for small banks, who either have no other wholesale funding opportunities, or have to pay higher premiums for their higher counterparty risk. In addition to the cost benefit, the member can borrow in various structures. The borrowing interest rates can be either fixed or floating, and the maturity ranges from overnight to as long as 30 years.

To fund advance borrowing, the FHLB issues consolidated obligations of the system in the public capital markets, and all regional FHLBs are jointly liable for all system-consolidated obligation debt. Although FHLB obligations are not explicitly guaranteed or insured by the federal government, their status as a government-sponsored enterprise accords certain privileges and enables the FHLB to raise funds at rates slightly above comparable obligations issued by the US Department of the Treasury. As of 2018, the total outstanding FHLB advances amount to \$729 billion, which makes the FHLB a fundamental part of the US mortgage market.

2.2   Data

The primary unit of observation in this paper is the bank *branch*, instead of the bank (a group of branches). This is mainly because the boundary of banks changes after mergers, while the boundary of individual branches is stable across time. FDIC Summary of Deposits (SOD) provides an annual survey of all branches for each FDIC-insured institution since 1994, including the ownership of each branch. In addition, SOD records each branch's street address, which I map to its census tract using GIS software. I will focus on the sample period between 1994 and 2016.

The Federal Housing Finance Agency website publishes the roster of all FHLB member institutions every quarter, from which we can find the membership status for a bank in a certain year. Bank merger activities are from the FDIC Report of Changes. In section 3, I will elaborate how I construct the multiple-target merger sample.

To measure the mortgage lending outcome for each branch, I combine three loan-level data sources: Home Mortgage Disclosure Act (HMDA) data, ATTOM and McDash. HMDA surveys cover 90% of mortgage origination in the US, and provide information on the lender and the census tract where the collateral is located. ATTOM data provide transaction and assessor information including loan performance data (i.e., prepayment and default), lender names and exact location. McDash data provide comprehensive information on the metrics of the mortgage (including interest rates, credit scores, loan-to-value ratios, product types and ex post performance). However, there is no unique identifier of mortgages across the three difference datasets. To connect them, I follow Bartlett, Morse, Stanton, and Wallace (2018) and exploit overlapping variables within these datasets to construct a merged data set of mortgages with lender identifiers, borrower characteristics, product metrics, and performance information, with a statistical-learning algorithm.

However, to measure the mortgage lending outcomes of a bank branch, we need to know the originating bank branch. Unfortunately, HMDA does not record the originating branch within each bank, which is crucial for this paper's purpose. I instead geocode each mortgage's property address using GIS software, and assign it to the closest branch of its lender, assuming each mortgage is originated by the nearest branch of the lender.

To explore the spillover effect of public funding access, I define the local market as the census tract where the bank branch is located, as in Nguyen (2019). These are defined by the US Census Bureau to be small, relatively permanent statistical subdivisions of a county. Specifically, census tracts are defined to optimally contain 4,000 inhabitants and therefore vary in size across urban and rural areas.[10] The mortgage-branch matching results show the median distance from a branch to the mortgage borrowers is around three miles, which indicates that the tract captures most of the effect of a structural change to a bank branch. In the robustness part in section 6, I look at the spillover effect at various distances, and find most of the effect is kept within ten miles from the treated branch.

3 Empirical Strategy

The empirical challenge in estimating the effect of accessing wholesale funding through FHLB membership is that the FHLB application decision is endogenous to the banks' economic conditions. Banks that are on an expanding trajectory tend to apply for FHLB membership to secure more funding sources, and thus a naïve event study would overestimate the effect of joining the FHLB. As a solution to this endogeneity problem, I explore the exogenous FHLB funding access change caused by bank mergers. Specifically, if FHLB member bank A acquires non-FHLB member target B, then the branches of the target bank B will operate under bank A and automatically get access to FHLB advances after the merger. But the change of bank B's branches mixes two effects: a merger effect (managerial change and access to other funding sources) and an FHLB effect. To achieve identification, I further consider multiple-target mergers, where the acquirer bank simultaneously acquires multiple target banks, and the target banks differ in their FHLB membership status. I rely on within-merger comparisons between target banks (branches) that have access to FHLB advances prior to the merger and those that do not, to difference out the merger effect. The identification assumption is that the target banks in multiple-target mergers share comparable trends regardless of their FHLB membership.

Figure 1 illustrates the identification strategy with a sample merger. The acquirer bank (dots) was seeking to expand its geographic footprint into the suburban areas by acquiring two small banks.

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[10]Since the population would change across different years, the boundaries of tracts are revised every 10 years in the decennial census. This paper uses the tract system in the 2000 Census, since the majority of the events are in 2000-2010, and crosswalk variables in other systems to the 2000 census tract.

The treated bank branch (cross) was not able to tap into FHLB advances before the merger, but could do so thereafter, while the control bank branch (triangle) already had FHLB access. Additionally, both target branches experience similar organizational change due to the merger. Therefore, the within-merge difference-in-differences strategy could identify the effect of getting access to wholesale funding provided by the FHLB.

3.1 Multiple-Target Merger Construction

To construct multiple-target mergers, I first use the change of branches' ownership from FDIC Summary of Deposits to identify all the mergers in the sample period. Noting that this period experienced a wave of substantial bank consolidation within the same bank holding company due to the relaxation of interstate branching restrictions, I drop all mergers whose target and acquirer belong to the same bank holding company, so that what remains are bank mergers that involve a change of the ultimate owners.

I then define a multiple-target merger if the same acquirer bank merges with more than one target bank in the same year.[11] All targets that are established less than four years before the merger, or closed less than four yeas after the mergers are dropped, to guarantee I have a balanced panel four years around the mergers. I further focus on all multiple-target mergers in which the acquirer is an FHLB member, and there is at least one FHLB member and at least one non-FHLB member in the target banks. The final sample contains 174 multiple-target merger events, which span the full sample period. Figure 2 plots the counts of multiple-target mergers in the sample period. The events are evenly distributed with slightly more happening before 2005, since there were still many small banks in the potential target pool that had not joined the FHLB in the earlier period.

3.2 Summary Statistics

Table 1 tabulates the characteristics of the sample banks, as well as their census tracts. The sample contains 174 multiple-target mergers. 250 target banks are not FHLB members before they are acquired, and 254 target banks are. The non-FHLB targets have 2051 local branches operating, while the FHLB targets have 1170 branches.

Panel B of Table 1 exhibits the bank characteristics of the two groups of targets. From the results, we can see the targets are mostly of small to medium size, with about $13 billion in total assets and $9 billion in deposits on average. The non-FHLB targets have 60% of their lending in real estate, of which 31% are mortgages. The FHLB members' position in real estate is slightly higher, at

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[11]Due to the data feature, I define the year to match the reporting cycle of FDIC summary of deposits, from the mid (June 30th) of last year, to the mid of this year. For example, mergers happening from July of 2002 to June of 2003 are considered to be in the same year 2003. This is to cater to the fact that FDIC report the detailed branch level information as of June 30th of each year, which would be the key for my mortgage assignment algorithm.

the 65% level, of which 32% are mortgages. This is consistent with the story that banks with a larger real estate position have a higher propensity to join the FHLB. But the difference in our sample is much smaller than the general case, and statistically insignificant, since the acquirers tend to acquire banks with similar characteristics. As another important component, non-FHLB targets have 16% of their investment in commercial and industrial lending (C&I), while the FHLB targets invest 14%. Both groups of targets have a very low non-performing loan ratio (1-2%) and loan loss rate (2%).

Column (3) calculates the difference of columns (1) and (2) within each merger event. Column (4) reports the p-value of the hypothesis test that this difference is zero. Since my identification assumption is that the non-FHLB and FHLB target banks are comparable along all dimensions except for FHLB membership within each merger, we should focus on the within-event differences. The results in columns (3) and (4) indicate that the treated and control groups have similar characteristics. Although we cannot exploit all possible features, especially for unobserved information, this is a reassuring sign that we are using a quite balanced sample for our exercise.

Now let us examine the markets in which the two groups of banks are located. Figure 3 plots the geographical footprints of the target banks, where the crosses are the branches of non-FHLB members before the mergers, and the triangles are those of FHLB members. We can see they spread out across the nation, and represent the bank population well.

Panel C of Table 1 presents the socio-economic features for the locating census tracts in 2000. Again columns (3) and (4) show that the treated targets are located in similar markets as the control targets. The median income for the both groups is around $45k. Both groups of tracts have 62–64% home owners, 18–20% minorities, 69% mortgagers, and 64–65% educated population, defined as people with at least some college education. I also compare the median income of the locating county and the relative ratio of income to this county benchmark. The control bank branches tend to be located in higher income tracts relative to the county, but the difference is not statistically significant. In terms of bank penetration, the tracts in our sample have four to five local bank branches.

3.3 Empirical Specification

I use a generalized difference-in-differences framework to compare the mortgage lending of the target banks in the treated and control groups before and after mergers, and allow for time-varying trends based on premerger tract characteristics. In such a framework, the identification assumption is that the two groups of target banks share parallel trends: absent the FHLB membership difference, outcomes of the treated and control banks would have evolved along the same path. To facilitate transparent examination of any pre-trends in the data, I estimate a year-by-year difference-in-differences and

present all my results as event study plots. The primary specification is

$$y_{it} = \left(\delta_{E(i)} \times \lambda_t\right) + \left(\delta_{E(i)} \times \gamma_i\right) + \left(\beta + \sum_\tau \beta_\tau D_{it}^\tau\right) FHLB_i + \gamma X_{iz(i)} + e_{it}, \tag{1}$$

where y_{it} measures the outcome variable for bank branch i in year t; $\left(\delta_{E(i)} \times \lambda_t\right)$ are event-by-year fixed effects; $\left(\delta_{E(i)} \times \gamma_t\right)$ are event-by-branch fixed effects; D_{it}^τ is a dummy equal to one if year t is τ years after merger $E(i)$ is completed; $FHLB_i = 1$, if branch i belongs to a bank that is not an FHLB member before the merger; $X_{iz(i)}$ include all control variables for branch i and its locating tract $z(i)$, including fraction of minority, fraction of college-educated, median income, the number of branches as of the year preceding the merger, as well as county-year fixed effect. Here, τ ranges from -6 to 8, and standard errors are clustered at the event level. The coefficient of interest is β_τ, which measures the difference, conditional on controls, in outcome y between treated and control banks τ years after the merger.

4 Effects of Public Funding on Individual Banks

The next two sections illustrate the reduced form results of banks getting access to public funding. This section will focus on the effect on the treated bank, while the next section discusses the effect to the local market structure and outcomes.

4.1 Bank Mortgage Lending

This section presents evidence for the effect of the access to external wholesale funding (FHLB advances) to the mortgage lending of the target banks. Figure 4 provides the template used for the event study results. It plots the β_τ estimated from equation (1), where the dependent variable is the number of mortgage originations. The bars show the 90 percent confidence intervals. Notice, $\beta_\tau > 0$ indicates that more mortgages are originated by the treated banks relative to controls τ years after a merger. The coefficients in the shaded area are estimated from a balanced panel, while the data outside are not balanced because the target banks are not yet established, or closed.

Figure 4 shows that up to six years prior to the merger, the non-FHLB member banks share the same trend with FHLB members in the number of mortgage originations. However, the relative origination counts dramatically increase in the year of the merger, and this origination increase persists over the following years. On average, each branch of the treated banks originates 9.8 more mortgages, off a baseline of 60 mortgages, after they get access to FHLB advances. In another word, access to FHLB funding leads to a 16.3% increase of mortgage originations.

This indicates that the treated banks are indeed financially constrained before getting support

from external funding. In theory, financial frictions would force banks to scale back from profitable projects for three reasons. First, financial constraints would impose a shadow cost on top of the direct funding cost, and make the banks' mortgages less attractive. Such a price effect will be shown in the next subsection. Beyond this, having inadequate funding sources prevents the banks funding all good investment opportunities that they can find. A more subtle reason is that inadequate funding sources also make it hard for banks to maintain their relationship with customers, so the banks have to incur more effort or cost to find qualified borrowers. After this friction is relaxed by external funding sources, the mortgage origination increases substantially.

While the effect on mortgage originations is substantial, we need to be aware of a caveat, that the banks in my sample are small, and tend to have a small mortgage lending base. Thus their growth potential in mortgage lending tends to be higher than a typical bank in the general population, so we need to be more conservative about the result in terms of external validity. In subsection 4.4, I will demonstrate this heterogeneous effect within my sample. And in the structural model, the effect to the full range of banks will be quantified after imposing structural assumptions on their cost functions.

The total mortgage origination measure includes securitized mortgages which the banks would sell to the securitization pipeline (most of the time, GSEs) shortly after origination, and those which the banks would hold on their balance sheet. I also investigate the effect of FHLB funding on both business models of mortgage origination in Figure 5. Panel (a) depicts the effect on securitized mortgages. Banks issue 5 more securitized mortgages, which corresponds to a 20% increase. Panel (b) focuses on the mortgages that are held on banks' balance sheet, and they increase by around 15% (or 5 in absolute counts) in the first five years after the banks join the FHLB. While both business models benefit from public funding access, the growth on securitized mortgages is slightly higher. This is consistent with the fact that mortgage securitization is more exposed to liquidity shocks (Stanton, Walden, and Wallace, 2014), and FHLB advances are a ready solution for the shortage of short-term funding.

4.2   Mortgage Interest Rates

This subsection looks at the effect of FHLB funding to mortgage interest rates. The same event study for mortgage interest rates is shown in Figure 6. After mergers, the treated banks lower their interest rates by about 18 basis points.

There are two contributing factors that drive the results. First, the easing of financial friction increases small banks' lending capacity, and reduces the shadow cost of the finance constraints. For example, when the small banks are short of funding due to deposit deficiency, they have to raise the interest rates to drive down the potential demand of mortgages. Second, the external funding is itself

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cheaper than at least some banks' marginal cost of deposits. FHLB advances have rates comparable to risk-free rates, which greatly lowers the cost of funding for the those banks. As a result, the recipient banks lower their mortgage interest rate and pass this benefit to their borrowers.

4.3 Effect on Mortgage Profile

This subsection explores the composition change of mortgage profiles after a bank gets access to FHLB funding.

Figure 7 plots the effect of FHLB funding access to the composition change of lenders' mortgage profiles. To interpret the magnitude of the effect more easily, the estimates in Figure 7 are from a less flexible version of the difference-in-differences regression:

$$y_{it} = \left(\delta_{E(i)} \times \lambda_t\right) + \left(\delta_{E(i)} \times \gamma_i\right) + \left(\beta + \beta_{POST} POST_{it}\right) FHLB_i + \gamma X_{iz(i)} + e_{it}, \tag{2}$$

where $POST_{it}$ is a dummy equal to one if year t occurs after merger $E(i)$, and all other variables are as previously defined.

The upper panel reports the change in the distribution of mortgages of different interest types. The outcome variables are the shares of mortgage originations for each interest rate type. One striking pattern is that the banks tilt more toward fixed-rate mortgages after they get access to FHLB advances. The position increases by 5% off the baseline of 83%. Correspondingly, their position in adjustable-rate and other types of mortgages drops significantly.

We know that fixed-rate mortgages are predominately preferred by US mortgage borrowers, since they shield the borrowers from the risk of interest rate increases. Such interest rate risk is instead shifted to the lenders, especially for the lenders who want to hold the mortgages on their balance sheet. And such risk is one-sided, since the borrowers have an embedded option to refinance if the interest rate drops. If the banks use floating-rate deposits to fund such mortgage lending, they have to face substantial risk due to interest rate fluctuation. What is worse, limited access to derivative markets and lack of economies of scales make many smaller lenders even less capable of managing their exposure to this interest rate risk. As a result, these banks that heavily rely on deposit funding are either less likely to offer fixed-rate mortgages, or have to charge higher interest rates to compensate for their risk exposure.

After the banks get access to FHLB funding, they can directly fund their fixed-rate mortgages with fixed-rate funding. In other words, the flexible structure of wholesale funding helps banks manage their interest rate risk, and issue more products with the consumer-preferred interest type. This explains why we see a spike in the fixed-rate mortgage position. In fact, FHLB advances give banks a chance to outsource their risk management burden. For many banks, the availability of

various structures of external funding is as important as the availability itself.

The middle panel of Figure 7 presents the composition change across different buckets of credit scores. The FICO profile of the borrowers seems quite stable before and after the mergers. This refutes the hypothesis that banks would expand to low-risk borrowers after getting access to low-cost funding. On the contrary, if anything, banks tend to lend more to borrowers with very high FICO scores.

The lower panel explores the change of LTV profile. While there is not much change for the loans that have LTVs above 80%, there is a strong shift from low LTV to high LTV for loans below 80% LTV. The 80% threshold is important here because it is one of the many requirements for a loan to be qualified for a GSE (Fannie Mae or Freddie Mac) guarantee. Conditional on these loans being GSE-guarantee eligible, the treated banks would grant more credit to the same borrowers after they get access to the wholesale funding. Again, this is consistent with the financial friction story, and such evidence suggests that the lenders do not only ration credit on the extensive margin, but also do so on the intensive margin.

4.4 Heterogeneous Effect on Banks of Different Sizes

How do banks of different sizes react to the access to FHLB funding? I split my sample banks into two groups: regional banks with total assets above \$1 billion at the year before merger, and community banks with total assets below \$1 billion.[12] I then run the same regression as specified by equation (2), but interact $FHLB_i$ with the indicator of the size category that the bank belongs to. The results are displayed in Table 2. Column (1) and (3) report the average effect for the full sample (same as in Figure 4 and 6), while columns (2) and (4) report the effect for regional banks and community banks, respectively. Below each point estimate, the row "relative to baseline" reports the size of the effect relative to the baseline of each outcome variable at the year before merger.

The results show community banks originate 12 more mortgages off the baseline of 57, while regional banks originate 9 more mortgages off the baseline of 61. Thus, lending grows more for smaller community banks both in absolute counts and relative to the baseline. The same heterogeneous pattern can be found in the effect to mortgage interest rates. Community banks reduce their interest rates by 29 basis points, while the regional banks' rates go down by 16 basis points.

This heterogeneous effect pattern is consistent with the well documented fact that smaller banks have more funding challenges in general. They usually have to pay higher interest to the depositors for the following reasons. First, small banks have a limited branch network, which makes it less

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[12]In a later section, I will group the banks into three size categories: national, regional and community. The national banks are those who belong to a bank holding company that ranks top four in combined total assets. So the strict definition of regional banks should be all non-national banks with total assets above \$1 billion. But in my sample, all target banks are non-national, and thus only fall into the other two size categories.

convenient for the customers to withdraw cash. Second, the perception that big banks have an implicit government guarantee puts small banks in a difficult position for attracting depositors, especially for those deposit products that are not insured by FDIC (Jacewitz and Pogach, 2018; GAO, 2014). In addition, small banks have to confront higher costs or are completely excluded from external financing, due to their limited scope for diversification (Kroszner, 2016).

A very similar funding structure also exists in the private market, and is commonly referred to as warehouse lines of credit. The small banks can alternatively turn to warehouse lenders and do collateralized borrowing as they do with the FHLB. However, the warehouse lenders would charge a higher cost for the small banks for their greater counterparty risk. In this sense, FHLB levels the playing field for small banks' wholesale funding by offering low-cost and non-discriminatory funding to all its member institutions.

Why does the FHLB not do risk pricing, as the private lenders do? In fact, the Federal Home Loan Bank Act requires the FHLB to give fair and non-discriminatory rates to all its members.[13] This is a crucial feature of the government-sponsored funding facilities, that has a profound effect on the industrial organization of mortgage lending as we will see in section 5.

5   Effects of Public Funding on Local Mortgage Markets

This section will further explore the spillover effect of banks after getting access to FHLB funding. Specifically, I will focus on the effect on market competition, and illustrate how strengthened local banks propel market competition.

5.1   Market Concentration

I look at the effect of FHLB membership to the local market concentration measure (Herfindahl-Hirschman Index[14]). Here the market is defined as the census tract where the bank branch is located. In the example merge sample, the markets are the colored tracts as shown in Figure 1. I choose this small geographical unit to make sure I will have enough statistical power to identify the spillover effect from my natural experiment. After a local bank gets FHLB funding, it is able to better compete with its competitors in the local market. For example, it could lower its mortgage interest rates or closing fees, or run more advertising campaigns to market their mortgage products. As shown in Figure 8,

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[13]The term 7(j) in Federal Home Loan Bank Act requires the board of directors shall administer the affairs of the bank fairly and impartially and without discrimination in favor of or against any member, and shall, subject to the provisions hereof, extend to each institution authorized to secure advances such advances as may be made safely and reasonably with due regard for the claims and demands of other institutions, and with due regard to the maintenance of adequate credit standing for the Federal Home Loan Bank and its obligations.

[14]The local HHI is constructed from the share of each lender's mortgage originations. And it ranges from 0 to 100% (monology).

the concentration measure in the market falls by around 1.5 percentage points, from the baseline of 15%. Since the treated bank tends to be a small lender in the local census tract, its expansion due to better funding structure intensifies the market competition significantly.

Here I need to clarify that the market effect I present here considers all types of mortgage lenders. Table 1 shows there are on average 4–5 bank branches in the sample census tracts, which might lead to a misconception that there are only 4–5 lenders in the local mortgage markets. Actually, there are potentially more lenders, for the following reasons. First, even though distance is important for mortgage lending, it is still often the case that banks lend across census tracts, since a census tract is quite a small geographic subdivision. Second, there might be lenders that are not commercial banks, such as credit unions and non-depository mortgage companies (or shadow banks). Especially after the crisis, non-depository mortgage companies' market share grows very fast due to a regulatory environment favorable for these lenders. HMDA data survey almost all mortgage lenders, so the market effect that I present in this paper involves all market participants.

5.2 Competitors' Reaction in Mortgage Rates

The competition can take different forms, such as price competition or advertising campaigns. Table 3 illustrates the evidence consistent with price competition, by exploring how the market competitors react in their pricing strategy after one local bank gets access to FHLB funding.

Column (2) illustrates that the treated banks lower their mortgage rates by 18 basis points after joining the FHLB. Their competitors react to the change by lowering their interest rates by 7 basis points on average, as in shown in column (3). As a result, the market level mortgage rates fall by 8 basis points.

5.3 Aggregate Mortgage Credit Supply

Figure 9 shows the effect on mortgage origination in the local market. If a local bank branch gets access to FHLB advances, the locating census tract will see 10 more mortgage originations, or a 5% increase, in the later years. This suggests the treated bank is not just crowding out the business from its competitors. It is able to extend credit to otherwise unsatisfied borrowers through its relationship network. This is consistent with the relationship banking literature, that emphasizes that it is costly and slow for banks to build relationships with their borrowers. So if a financially constrained bank is not able to satisfy the demand of its clients, and the unfilled demand cannot be easily filled by other non-constrained lenders.

5.4 Market Structure

To dig into the interaction between the treated banks and the local market, I look at the effect on lenders of different sizes. I first categorize all competing lenders into three groups: national banks, other small banks, and non-banks. The national banks are those who belong to a bank holding company that ranks top four in terms of combined total assets. Small banks are all non-national banks, including both regional and community banks. Here I exclude the treated banks to focus on the competition effect. Non-banks are all other lenders, among which most are shadow banks.[15] I then normalize the mortgage originations for each group of lenders by the baseline market mortgage originations at the year before mergers, and regress these normalized mortgage originations with estimating equation (2).

The results are reported in Figure 10, where the three panels (upper, middle and lower) correspond to different mortgage products. The upper panel plots the effect for all mortgages. We can see the entire market grows by around 5%, in which two-thirds of the credit expansion directly comes from the bank that gets access to FHLB advances through mergers. This measures the direct effect caused by the better funding structure of the treated banks. The remaining third comes from the competing lenders through a competition effect. Specifically, the competing lenders are pushed to lower their mortgage rates, which increases their credit provision. This suggests that FHLB funding does not only benefit the treated banks, but also exhibits a positive spillover effect to the local market. If we look into the competitors, we can see other small banks are driving most of the competition effect. Their mortgage originations grow by almost 2% relative to the baseline market lending, which contributes 40% of the aggregate market growth. The national banks instead lose a significant share (1%) of the market.

As I will illustrate more extensively in the next subsection, national banks tend to apply a uniform pricing strategy across different markets. Their mortgage rates involve a centralized decision market process, so are less responsive to the change in local market structure. Other small banks, on the other hand, are more vigilant to the changing market conditions, so we can see the small banks are gaining market share, while national banks' market share is eaten by other lenders. Shadow banks also seem to react to the intensified market competition and gain some market share, but the effect is not statistically significant.

I then carry out the same exercise for mortgages of different types. The middle panel of Figure 10 plots the effect for refinance mortgages, where the borrowers seek to replace their existing mortgages with new ones. Issuing this type of mortgage usually involves less information acquisition, so the service is quite standard, and different lenders are more homogeneous from the borrowers' point of

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[15]Here non-banks also include credit unions. But they have very small market share.

view. In this sense, the price competition is more important for refinance mortgages. And indeed, we see that only about half of the market growth is driven by the treated banks, and the competition effect plays a more important role. Again, other small banks account for most of the competition effect.

The lower panel plots the effect for the other mortgage type—purchase mortgages, where the borrowers seek financing to purchase their houses. To issue such mortgages, the lenders need to collect more information from the borrowers and go through a lengthy screening process. For this reason, the service is more customized and thus less homogeneous across different lenders, so the lender-borrower relationship is key to this process while price plays a less important role. The regressions show that almost all market growth of purchase mortgages comes from the treated banks. The price competition is not as salient in this case.

5.5 Market Responsive to Local Economic Shocks

This subsection aims to test the effect on pricing efficiency. This is based on the premise that small banks are more flexible in making decisions and tend to be more responsive to local economics shocks. If a small bank in the local market is strengthened by external funding and takes more market share, then their regional adjustment of interest rates based on local economic conditions is more relevant for the borrowers. Therefore, market pricing efficiency will improve. This section first verifies the premise that small banks are indeed more responsive to such information on regional risks. After that, I will illustrate how extending external funding to these small banks affects the pricing responsiveness of the local economic conditions.

A Measure of Local Default Information. In order to examine whether mortgage rates vary with local economic conditions, we need to define measures of local economic activity observable to lenders that could potentially be used in their pricing decisions. I follow Hurst, Keys, Seru, and Vavra (2016) and use default rate in the past two years in the locating county to proxy for local economic conditions. First, a mortgage is defined as defaulted if the borrower is 60 days delinquent at least once, which is one of the best predictors of repayment distress. Specifically, within each county c in year t, I measure the fraction of loans originated during the prior two-year period that defaulted at some time between their origination and the beginning of the current period t. I refer to this measure as $d_{c,t}$. This lagged delinquency is a good measure of local economic activity both because it is a summary statistic for many economic factors that could predict future default (e.g., weak local labor markets, declining house prices) and because it is easily observable by lenders.[16] This measure of local

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[16] Here I use a county level measure to capture the economic condition in the regional market. Although there are still idiosyncrasies within a county, the county is generally viewed as a connected market that has a shared labor force base and a common house price trend. The results are robust to alternative choices, such as MSA.

default information has great predictive power of the realized local default, as elaborated in appendix A.1.

Residualized Interest Rates. I want to illustrate spatial variation in mortgage rates and show how this variation correlates with spatial variation in predicted future mortgage default rates for lenders of different sizes. However, interest rates and default rates could potentially differ spatially just because borrower or loan characteristics such as FICO score or date of origination vary spatially.[17] To formally control for these factors, I purge the variation in mortgage rates and subsequent default rates of spatial differences in borrower and loan characteristics. To do so, I fit the mortgage rates into the following equation with the loan-level micro data:

$$r_{it} = \lambda_t + \sum_\tau \beta_\tau Z_{it}^{\text{FICO} \in \tau} + \sum_\tau \delta_\tau Z_{it}^{\text{LTV} \in \tau} + \sum_\tau \psi_\tau Z_{it}^{\text{Lien} \in \tau} + \sum_\tau \phi_\tau Z_{it}^{\text{Interest Type} \in \tau} + \tilde{r}_{it}, \quad (3)$$

where r_{it} is the loan-level mortgage rate for a loan made to borrower i in quarter t. And I discretize the FICO distribution with a bin width of 20, and $Z_{it}^{FICO \in \tau}$ is a dummy equal to one when the borrower i's FICO score falls in bin τ. This would give the fitting structure great flexibility to allow for the non-linear relationship between interest rates and credit scores. Similarly, I discretize the LTV distribution with a bin width of 20%, and $Z_{it}^{LTV \in \tau}$ is a dummy equal to one when the loan-to-value ratio falls in bin τ. In addition, I also control interest rate type and lien status. λ_t is the month fixed effect.

Table C1 in the appendix reports the results of the these regressions. We can see that this flexible structure explains as much as 71% of the variation in the mortgage interest rates. After controlling for these loan and borrower characteristics, the following analysis will use the residualized interest rate $\tilde{r}_{it}$ to explore the spatial variation.

Are Small Banks More Responsive to Local Economic Shocks? To show this empirically, Figure 11 plots the relationship between the residualized interest rates $\tilde{r}_{it}$ and the local lagged default rates $d_{c(i),t}$, for three groups of banks : national, regional, and community banks. The slope of the fitted line indicates the degree of regional pricing. I divide the mortgages into two subsamples: GSE mortgages that are not securitized by the two housing GSEs (Fannie Mae and Freddie Mac), and non-GSE mortgages, since banks do not have full control or great incentives to set optimal rates for GSE mortgages (Kulkarni, 2019).

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[17]For example, borrowers with lower credit scores empirically face higher interest rates and are more likely to later default. If borrower creditworthiness varies spatially, this could explain some spatial variation in observed mortgage rates and default rates. What I am after, however, is whether interest rates and the predictable component of default rates vary spatially after conditioning on borrower and loan characteristics. A borrower with a given characteristic may be more likely to default in one region relative to another because overall economic conditions differ across regions. This paper seeks to explore whether a given borrower would pay a higher interest rate when taking out an otherwise identical loan in a high risk rather than a low risk location.

For non-GSE mortgages in panel (a), we can clearly see that national banks barely have regional shocks priced into their products, but the regional and community banks are much more responsive to local default rates.[18] I also find that GSE mortgages do not price regional risks for each size category, as shown in panel (b). This is consistent with Hurst et al. (2016).

Although the underlying rationale for this data pattern is not the focus of this paper, Gan and Riddiough (2008) provides a rational framework where the insights could apply in this scenario. In their model, the lenders that have information monopoly are reluctant to reveal their information through risk based pricing, to prevent potential entries. In addition, I provide more analysis in appendix A.2 to show that regional pricing could improve price efficiency, so a profit-maximizing lender should implement regional pricing if the cost of doing so is not very high.

FHLB effect on market responsiveness to local economic shocks. Table 4 reports the change of interest rates at the market level across heterogeneous markets. The markets are grouped into safe and risky markets, according to their local default rate at the county level in the past two years. Markets are defined as safe if located in a county where the mortgage default rates in the past two years are below the national median, or defined as risky otherwise. Column (1) and (2) still use the difference-in-differences specification as in equation (2), and report the effect for safe and risky markets, respectively. We can see that the market interest rate in the safe market drops more than in risky areas. Column (3) further interacts Post×$FHLB$ with the indicator of safe markets (triple diff), and confirms that the reaction difference between safe and risky markets is significantly different. Since small banks are gaining more market share in the safe markets, their representation in safe markets increases more, and thus their influence on the market interest rate is higher. This will make the mortgage interest rate more reflective of the local default risk, and pricing efficiency is increased.

Columns (4) and (5) apply the triple diff regression to GSE securitized mortgages, and non-GSE securitized mortgages respectively. The effect is entirely driven by the non-GSE mortgages.

6 Robustness Checks

This section carries out a series of robustness checks to rule out identification concerns.

6.1 Placebo Test 1: Small Business Loan Lending

This subsection exploits the effect of FHLB funding on small business loans of less than 1 million dollars, as a placebo test. Since FHLB advances require mortgages as collateral, we could expect that

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[18]In terms of magnitude, if the lagged default rate of a local county is 1% higher than other places, the local national banks would not raise its mortgage rates, while the regional banks would raise their rates by as much as 16 basis points, and community banks would their rates by 18 basis points.

the effect on the mortgage lending is the most salient, and the effect on small business lending would be minimal. Using Community Reinvestment Act (CRA) public data, I apply the same assigning algorithm to link each small business loan to its originating bank branch. Figure 14 shows that FHLB advances seem not to affect the lending of small business loans.

There are two offsetting forces that are driving the effect on small business loans. On the one hand, a dampening force arises because FHLB funding is better tailored for mortgage lending, which might make the recipient banks more willing to switch to the mortgage business. On the other hand, commercial lending could also benefit from the relaxation of financial constraints. The insignificant effect on small business lending indicates that the two forces are completely offsetting.

6.2 Spillover Test

One might be concerned that the effect of FHLB funding access to the local market comes from the selection of bank locations, instead of treated banks joining the FHLB. In this subsection, I implement the spillover effect to verify that the effect is really coming from the structural change to the target banks, to rule out the concern of selection of different markets. The spillover test could also illustrate how far the target bank's effect reaches, which can justify my choice of census tract as the market definition.

Specifically, I draw a series of concentric rings around the target banks, as illustrated in Figure 12. Each ring has a band width of two miles. To measure the outcomes in each ring, I crosswalk the overlapping census tracts to the featured rings.

For each ring, I estimate equation (1) where the dependent variable is mortgage originations per square mile. Figure 13 plots the results for different rings, and shows that the effect is very localized. The impact is most severe in the tract where the branch is located, and strikingly, the magnitude of the effect decreases nearly monotonically as the distance from the target branch increases. This pattern is remarkably consistent, both qualitatively and quantitatively, with existing evidence on the local nature of mortgage lending markets.

7 A Structural Model of Mortgage Lending

I develop and estimate an equilibrium model of the local mortgage markets, with three objectives. First, due to my identification strategy, the markets I have studied in the reduced form exercise are just a limited and non-representative sample. By developing a model framework, I am able to uncover the cost heterogeneity for all banks, and apply counterfactual exercises to the full sample of banks across the nation. Second, the model allows me to study unobserved policy counterfactuals (e.g., shutting down the FHLB, or the FHLB charging different prices for different banks), from which we

can comprehensively analyze the FHLB's impact. Third, the structural model helps me to evaluate many unobserved outcomes, including borrowers' welfare and the pass-through of the cost reduction from the FHLB.

7.1 Model setup

7.1.1 Geography and Market Participants

The economy has M segregated markets. In each market m, I_m heterogeneous households indexed by $i \in \mathcal{I}_m$ look for mortgage financing from the K_m lenders, denoted by $k \in \mathcal{K}_m$. At each period t and market m, a regional shock $\delta_{m,t}$ is realized, and determines the local economic performance. In the empirical estimation, the market is defined at the CBSA-loan purpose level. For example, the borrowers who live in the city of San Francisco and look for mortgage refinancing (in a certain year) are considered to be in the same market and face the same set of banks supplying credit. The lenders include both banks and shadow banks. I group banks into three categories according to their size. Therefore, this model has four lender categories: national banks (nb), regional banks (rb), community banks (cb) and shadow banks (s). Let $g(k) \in \{nb, rb, cb, s\}$ denote the category that lender k belongs to.

Here my defined the geographical span of the market is CBSA, which is different but not inconsistent with my choice of census tract in the empirical part. Please note that I am not assuming that in the reduced form framework the effective market for a local bank branch is the census tract. It can be larger than census tract. But the effect on the locating census tract should be the most salient from an empirical point of view. In the structural model, since I do not model the effect of distance on lending, every census tract within the CBSA will have the same competition structure with the CBSA because they are just homogeneous subdivisions. So the structural model will predict that the competition effect is the same across all the census tracts within a CBSA. The only subtle problem is that distance is a feature of reality, and that is why I choose to look at the locating census tract in the reduced form exercise. But my structural model does not include it (to avoid complexity). This would only be a problem if I use census tract level reduced form results to calibrate my model, which I do not. I will just use the bank-level reduced form results to calibrate the model.

7.1.2 Mortgage Demand

In each market m, each household i chooses which lender to borrow from among all lenders in the market. The indirect utility that household i derives from lender k at period t depends on the interest rate the lender offers $r_{k,m,t}$, and the service it provides $q_{k,m} + \xi_{k,m,t} + \epsilon_{i,k,m,t}$. In this model, the lender offered interest rate $r_{k,m,t}$ is risk- and product-adjusted, so it does not depend on the borrower and

mortgage characteristics. In other words, I am modeling the baseline interest rate for each lender, on which they can add premiums according to borrower and mortgage characteristics (e.g. FICO scores, LTV, interest rate types). $q_{k,m}$ is the time-invariant component of the service quality for lender k's operation in market m (e.g. lender k's proximity to borrowers). $\xi_{k,m,t}$ captures the time-varying component of the service quality (e.g. processing time and screening efficiency). $\epsilon_{i,k,m,t}$ is borrower's i idiosyncratic preference of lender k (e.g. relationship between borrowers and the lender), and is assumed to be distributed *i.i.d.* Type I extreme value, which leads to the standard logit market share.

$$v_{i,k,m,t} = -\alpha_i r_{k,m,t} + \underbrace{q_{k,m} + \xi_{k,m,t} + \epsilon_{i,k,m,t}}_{\text{service}} \tag{4}$$

To characterize the extensive margin of the equilibrium credit, I assume each household has a reservation utility of $v_{0,m,t} + \epsilon_{i,0,m,t}$ with a standard normalization assumption $v_{0,m,t} = 0$, and they only choose to finance when $v_{i,k,m,t} > \epsilon_{i,0,m,t}$.

The borrowers' disutility coefficients α_i vary across the population. For example, a low-income household might have a higher elasticity to interest rates. Here I assume the coefficient α_i is random and has the following structure:

$$\alpha_i = \bar{\alpha} + \gamma(D_i - \bar{D}) + \sigma_\alpha \zeta_i \tag{5}$$

where D_i are the borrower's observed demographics, including their income and house prices. $\sigma_\alpha \zeta_i$ captures borrowers' unobserved characteristics (e.g. assets, risk-aversion, housing preferences), and ζ_i is assumed to follow *i.i.d.* standard normal distribution. This random coefficient assumption would allow a rich substitution pattern between different lenders, and enable me to match the data more flexibly. The demand parameters to be estimated are then $(\bar{\alpha}, \gamma_\alpha, \sigma_\alpha)$.

7.1.3 Mortgage Supply

In each market m, K_m lenders maximize their (expected) profits by setting the optimal price conditional on their marginal cost and perception of the borrowers' default risk. The (unconditional) net profit for each lender can be written as:

$$\max_{r_{k,m,t}} \pi_{k,m,t} = I_m S_{k,m,t} \bar{Q} \bar{T} \left[(r_{k,m,t} - c_{k,m,t} - \bar{l} E_k[d_{m,t}]) \right] \tag{6}$$

where $S_{k,m,t}$ is lender k's market share mortgage origination in market m and year t. For simplicity, I assume all mortgages have the same size $\bar{Q}$, and the same average life $\bar{T}$. The average life $\bar{T}$ maps

one-period net interest income to the total value of all future net income.[19] $\bar{l}$ is the annualized loss rate conditional on default, which is normalized by $\bar{T}$.[20] This loss includes both interest loss and principal loss.

Marginal cost. $c_{k,m,t}$ captures the marginal cost lender j incurs when originating the mortgage in market m during year t. It can be decomposed into three components:

$$c_{k,m,t} = f_t + c_{k,t}^F + c_{k,m,t}^O. \tag{7}$$

where f_t is the risk free rate that captures the time cost of the funding, $c_{k,t}^F$ is the lender-specific funding cost, and $c_{k,m,t}^O$ captures the market level variation in operating mortgage origination.

The funding cost of lender k depends on lender k's category and its access to the FHLB

$$c_{k,t} = \begin{cases} \mu_{g(k)} + \sigma_{g(k)}\omega_t & \text{if } k \notin FHLB \\ \min\{\mu_{g(k)} + \sigma_{g(k)}\omega_t, c^{FHLB}\} & \text{if } k \in FHLB \end{cases}. \tag{8}$$

If lender k does not have access to the alternative funding source (FHLB advances), its funding cost is drawn from a log-normal distribution ($\omega_t \sim logN(0,1)$). The two size-related parameters shift the cost distribution from a standard log normal distribution, where $\mu_{g(k)}$ controls the level of average funding cost (e.g. deposit interest), and $\sigma_{g(k)}$ governs its dispersion (e.g. exposure to funding shocks, such as deposit withdraws).[21]

If lender k is an FHLB member, its funding cost will be capped by the cost of FHLB advances c^{FHLB}. Here the FHLB is a steady wholesale funding source, and their advances are a substitute for lenders' deposit funding when they suffer bad deposit shocks. c^{FHLB} is the spread that the FHLB charges over the risk free rate that includes term premium, operational expenses, and the cost of posting collateral. In this sense, it is the effective cost of FHLB funding. For FHLB member lenders, FHLB advances cap their funding cost at the level of $f_t + c^{FHLB}$. They will fund their mortgages with FHLB advances when their instantaneous deposit cost is higher than the cost of FHLB advances.

Default rate. $d_{m,t}$ is the default rate of borrowers in market m, which depends on local economic conditions. Here, we are not considering borrowers' idiosyncratic risk (e.g. FICO and LTV) in pricing

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[19]Equation (6) strictly applies to the cases where the mortgage's principal amortizes according to a schedule that does not depend on the contractual interest rate. For example, let T be the contractual maturity of a mortgage product, $\{P_t\}_0^{T-1}$ be the beginning principal fraction for each period, and r_f be the risk-free rate, then

$$\bar{T} = \sum_{t=0}^{T-1} \frac{P_t}{(1+r_f)^t}.$$

But the real-life fixed-rate mortgages are amortized to guarantee a fixed payment for each month, which makes the principal schedule depend on the contractual interest rate. In this case, such representation is a close approximation.

[20]$\bar{l} = E[\mathcal{L}]/\bar{T}$, where $E[\mathcal{L}]$ is the expected loss rate conditional on default. For example, if the loss rate is 50% upon default, and the average life of a mortgage is 5 years, the annualized loss rate conditional on default $\bar{l} = 10\%$.

[21]Strictly speaking, $E[\mu_{g(k)} + \sigma_{g(k)}\omega_t] = \mu_{g(k)} + \sigma_{g(k)}e^{0.5}$, and $Var[\mu_{g(k)} + \sigma_{g(k)}\omega_t] = \sigma_{g(k)}^2(e-1)e$.

market specific baseline interest rates.

Motivated by the fact that different lenders respond to local economic shocks differently, as shown in Figure 11, this model assumes in a very parsimonious way that a lender's perception of local economic conditions is a function of the lender's size.

$$E_k[d_{m,t}] = \phi_{g(k)}\rho(d_{m,t-1} - \bar{\delta}) + \bar{\delta}, \tag{9}$$

where ρ measures the persistence of the local default rate. $\bar{\delta}$ is the national average level of default rate. $\phi(\cdot)$ is a monotonically decreasing function bounded by $[0,1]$. It governs a lender's perception of the local economic conditions, thus its responsiveness in pricing mortgages. We can see that if $\phi(\cdot) = 0$ (e.g., the big four national banks), the lender just prices their mortgage at the national default rate. On the other extreme where $\phi_{g(k)} = 1$, the lender fully adjust its interest rate to account for local economic conditions.

This is a very parsimonious way to model lenders' heterogeneous reaction to local shocks, but this representation can be well micro-founded. In appendix section A.3, I provide a micro foundation, which builds on the agency frictions between the lender management and local branch managers, a la Stein (2002), and attributes national banks' low responsiveness to local shocks to their great cost in verifying local branch managers' report on local default prediction.

7.2   Equilibrium

In equilibrium, mortgage demand is characterized by borrowers' choice of mortgage lenders, given the mortgage rates and lender service quality. Supply is characterized by the lenders' optimal decision on their offered interest rates. FHLB funding would affect the equilibrium interest rates by capping the funding cost of the member banks. The lenders are heterogeneous in two key dimensions: the cost structure (average cost and volatility), and the perception of the local default rate.

Mortgage Demand. Household i in market m maximizes its utility by choosing between all lenders available in the market. It also has the option not to borrow if its reservation value is higher than that offered by any lender. The distributional assumption of the idiosyncratic preference $\epsilon_{i,k,m,t}$ implies that the (conditional) probability that borrower i in market m at year t chooses lender k follows the standard logit form, as the integrand in equation (10). Integrating out the unobserved heterogeneity ζ_i gives us the market share of each lender:

$$S_{k,m,t} = \int_{\zeta_i} \frac{\exp(-\alpha_i r_{k,m,t} + q_{k,m} + \xi_{k,m,t})}{1 + \sum_{\iota=1}^{K_m} \exp(-\alpha_i r_{\iota,m,t} + q_{\iota,m} + \xi_{\iota,m,t})} dF(\zeta_i). \tag{10}$$

Mortgage Supply. The lender would set the optimal interest rate to maximize its expected

profit in equation (6). Solving the first order condition, we get the optimal interest rate

$$r_{k,m,t}^* = \underbrace{c_{k,m,t}}_{\text{Marginal cost}} + \underbrace{\bar{l}E_k[d_{m,t}]}_{\text{Risk premium}} + \underbrace{\frac{S_{k,m,t}}{\int_{\zeta_i} \frac{\alpha_i \exp(-\alpha_i r_{k,m,t}+q_{k,m}+\xi_{k,m,t})(1+\sum_{\iota \neq k} \exp(-\alpha_i r_{\iota,m,t}+q_{\iota,m}+\xi_{\iota,m,t}))}{(1+\sum_{\iota=1}^{K_m} \exp(-\alpha_i r_{\iota,m,t}+q_{\iota,m}+\xi_{\iota,m,t}))^2} dF(\zeta_i)}}_{\text{Markup}}.$$

(11)

The optimal interest rate has three components: lenders' marginal cost, risk premium and markup. The marginal cost varies within year t due to deposit fluctuations. The markup depends on the lenders' market power.

8 Estimation and Results

The model is summarized by equation (8), (11) and (10), and characterized by a set of demand parameters $(\bar{\alpha}, \gamma, \sigma_\alpha, q_{k,m})$, parameters in default prediction $(\rho, \phi_{g(k)})$, lenders' funding cost structures $(\mu_{g(k)}, \sigma_{g(k)})$, and the cost of FHLB advances (c^{FHLB}). In this section, I discuss the estimation procedures and identification strategies.

8.1 Estimation and Identification

Estimation proceeds in two steps. In the first step, I estimate demand parameters using data on mortgages originated across the US. In the second step, I estimate the supply parameters by targeting the FHLB effect in the reduced-form exercise, as well as other necessary moments.

8.1.1 Demand Estimation

I use mortgages originated between 2000 and 2015 from my HMDA-Attom-McDash merged sample to estimate the demand parameters. Since I only have the baseline interest rates for each lender in my structural model, I first residualize the mortgage rates using equation (3), where I factor out borrower and product characteristics, including credit scores, LTV, lien status and interest type. I then aggregate the mortgage level data to lender-market observations. A market is defined at the level of CBSA-loan purpose, e.g., mortgage refinances in the city of San Francisco. Following Buchak et al. (2018b), this paper also separates markets into mortgages originated for new purchases and mortgage refinances since a borrower looking for one type of mortgage financing is not looking for the other type. Borrowers can choose between all lenders in the market. In each CBSA-year, I include two demographic variables: log incomes and log house prices. Both variables are from the American Community Survey (ACS).

To capture the extensive margin of mortgage lending, I define market size in the same way as Buchak et al. (2018b). One tenth of the total number of households are looking for purchase mortgages, and all mortgagors are in the market of mortgage refinance.

I estimate the demand parameters in two steps. In the first step, I rewrite the equation (10) as

$$S_{k,m,t} = \int_{\zeta_i} \frac{\exp(-\gamma(D_i - \bar{D})r_{k,m,t} - \sigma_\alpha \zeta_i r_{k,m,t} + \lambda_{k,m,t})}{1 + \sum_{\iota=1}^{K_m} \exp(-\gamma(D_i - \bar{D})r_{\iota,m,t} - \sigma_\alpha \zeta_i r_{\iota,m,t} + \lambda_{\iota,m,t})} dF(\zeta_i). \tag{12}$$

With a generalized method of moments (GMM), I search over the (γ, σ_α) parameter space to minimize the predicted and the observed market shares of lenders. Here $\lambda_{k,m,t}$ is the market-year-lender fixed effects. In each GMM iteration, they are recovered by the contraction mapping method following Berry et al. (1995) and Nevo (2001). In the second step, we can recover $\bar{\alpha}$ and $q_{k,m}$ by running the regression:

$$\lambda_{k,m,t} = -\bar{\alpha} r_{k,m,t} + q_{k,m} + \xi_{k,m,t}. \tag{13}$$

Identification strategy. The interest rates offered by lenders might be reacting to some unobserved factors, which might bias the estimation in both steps of the estimation. To resolve this endogeneity problem, I construct a list of instrumental variables to instrument for the interest rates in both steps. First, I use the big four national banks' national interest rate to instrument for their mortgage rates in the local markets, by noting the fact that national banks apply the uniform pricing strategy across the nation. For example, JP Morgan's local interest rates in San Francisco are not reacting to the local demand factors, but are dictated by JP Morgan's national pricing strategy. I also use other lenders' mortgage characteristics to instrument for the lender's own interest rates following Berry et al. (1995). Specifically, I use other lenders' average proportion of fixed rate mortgages, and average LTV.

8.1.2 Supply Estimation

The estimation of supply side parameters is based on the optimal pricing equation. I assume lenders in the same category share the same cost and default perception parameters $(\mu_{g(k)}, \sigma_{g(k)}, \phi_{g(k)})$. This largely reduces the dimension of the parameter space, and increases the power of estimation. The tradeoff is that I ignore the heterogeneity of lenders within the same category, which is a second order issue in this paper.

The estimation uses the simulated method of moments (SMM). Specifically, the optimal pricing formula (11) allows me to simulate the interest rates charged by all categories of lenders, from which we can calculate the model implied moments. By minimizing the distance between the model implied and empirical moments, I am able to estimate the supply side parameters.

Identification strategy. The key parameter on the supply side is c^{FHLB}, which determines the effect of the FHLB on banks of different categories. My estimation procedure adds the FHLB effect on member banks' interest rates (for regional banks and community banks) in my reduced form into the targeting moments. The parameter c^{FHLB} will be mostly identified by these two moments (interest rate drops after joining the FHLB for regional banks, and community banks). I also add other moments from the data to discipline my structural model, including the mean and variance of the interest rates offered from lenders in each category and mortgage rate sensitivity to lagged local default rates. The former is mainly used to identify the distribution parameters of lenders' funding cost $(\mu_{g(k)}, \sigma_{g(k)})$, and the latter is mainly used to discipline the default perception parameters $(\rho, \phi_{g(k)})$.

8.2 Estimation Results

Figure 15 plots the estimated distribution of the funding cost for banks of different sizes, and the funding cost of FHLB advances. The black line represents the funding cost for the national banks, the blue line is for regional banks, and the red line is for community banks. We can see the national banks' funding cost is on average lower than the other two groups of banks. This is due to multiple reasons. First, the national banks have a large network of branches, which facilitates their deposit raising. Second, national banks are perceived to be "too big to fail", so the depositors are more willing to put deposits into them if they are concerned with the downside risk. This is especially important for their uninsured deposits (Jacewitz and Pogach, 2018; Egan et al., 2017). Other than the lower average funding cost, the national banks' cost distribution is also tight due to their well diversified deposit base, so they are less exposed to funding shocks. So the idiosyncratic deposit withdraws would net out in their branch network. This can also be due to their many private wholesale funding sources, including their many secondary market funding facilities (e.g. repo funding, asset backed commercial papers). The regional banks' cost distribution shifts towards the right, representing their higher funding costs, and the community banks' cost distribution shifts right even further.

Given this funding cost heterogeneity, the FHLB will have different effects on banks of different sizes, with a larger impact on community banks and less on national banks. The numerical simulation implies that the FHLB would effectively reduce the funding cost by 1 basis point for national banks, by 15 basis points for regional banks, and by 28 basis points for community banks. The effect looks smaller than what appears in the figure due to the competition in the market. In the market, lenders with higher funding costs would have smaller marker share, thus its effective weight in calculating the FHLB effect is smaller.

Here I want to point out that the cost of FHLB advances is mainly identified using the reduced form effect on regional banks and community banks. We actually cannot observe national banks in

the reduced form sample. The structural model enables me to recover the funding cost for the banks of all sizes, with which we can extrapolate the FHLB effect on national banks.

8.3 Model Fit

Figure 16 compares the empirical and the simulated interest rate distribution for banks of different sizes. Overall the model fits the data well along the three dimensions: the mean, dispersion, and responsiveness to local defaults of the interest rates. The main limitation is that the model is not able to capture the non-linearity of interest rates in markets with very low default rates. This is due to the linear assumption of banks' perception of the local economic conditions.

9 Counterfactual Analysis

In this section, I use the estimated model to study two counterfactual policy changes regarding the FHLB. The baseline is the current equilibrium, where more than 90% of banks are FHLB members, and the FHLB offers the same funding rate for all members. In these counterfactual policy environments, I evaluate the effect on aggregate mortgage originations, interest rates, as well as the market structure. With the structural model, we can also draw conclusions on the empirically unobserved outcomes, including borrowers' welfare and the pass-through of the cost reduction due to government intervention.

9.1 Counterfactual 1: An Economy without the FHLB

To fully capture the impact of the FHLB in the economy, I first study the case where the FHLB does not exist. In the reduced form exercise, we are only able to observe a partial equilibrium exercise that one local bank joins the FHLB. Such a change would have a smaller effect on the aggregate outcomes, including mortgage originations and interest rate, since the affected bank is only a small part of the market. As for the effect on the market structure, the comparison can go in either direction. On the one hand, only one bank's funding structure is changed, so the effect on the market structure is smaller. On the other hand, the affected bank tends to be small, and it pushes the market to be more competitive without any offsetting forces. If we change the funding structure for both small and big lenders, there might be an offsetting force to push the market to become more concentrated since the big lender also benefits from the FHLB. In this section, I am going to employ my structural model to quantify the effect of the FHLB in a general equilibrium setting.

The simulation implies that if the FHLB is removed from the economy, the average market interest rate would increase by 11 basis points, and aggregate mortgage originations will fall by

7.05%. A simple back-of-the-envelope calculation suggests that national mortgage originations will decrease by \$129.28 billion, and borrowers will have to pay \$13.55 billion more in interest payments.[22]

The impact of removing the FHLB is different for banks of different sizes, as shown in Figure 17. Community banks will be hurt the most, their interest rates will increase by 29 basis points, and they will therefore lose market share of 4%. The regional banks' mortgage rates will increase by 16 basis points, which would lead to a market share loss of 2%. The national banks, on the other hand, will benefit from the removal of the FHLB. Their interest rates will rise by 1 basis point, and they will have a market share increase of 2%. The lack of the low-cost wholesale funding gives the national banks' an advantageous position in the market since there is less competition. The measure of market concentration, HHI, will increase by 2.38 percentage points.

Figure 18 plots average market-level interest rates across markets with different local economic conditions. The x-axis is the local default rate in the past two years, and the y-axis is the average baseline mortgage rates for all lenders.[23] The solid line plots the pricing schedule for the current equilibrium with the FHLB, which is upward sloping, indicating the lenders are actively responding to the local economic conditions. The dashed line represents the same relation in the counterfactual without the FHLB. In this case, the responsive lenders (community and regional banks) lose some market share, and the uniform pricers (national banks) are more dominating. As a result, the market responsiveness to local economic conditions falls, so we see a flatter slope. This would have negative consequences. A decreased price responsiveness raises the degree of cross-subsidization from the safer markets to the riskier markets. This would increase the high-default markets' representation in the lending landscape, and raise the default rate at the aggregate level. Such a price distortion would suppress the aggregate credit supply.

My structural model also allows me to directly calculate borrowers' welfare, and it shows the borrower will lose 10.28% of welfare. The is due to a higher level of interest rates, and a constrained credit supply.

9.2   Counterfactual 2: The FHLB Offers Member Banks Different Prices

The large effect of the FHLB suggested by the first counterfactual exercise is due to the two roles that the FHLB plays in addressing market imperfections: shielding banks from liquidity shocks (the direct effect) and providing equal external funding access (the competition effect). Since the direct effect could also be achieved by the private market (e.g., warehouse lending), the competition effect is more informative for the value of public provision of wholesale funding.

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[22]The back-of-the-envelope takes the aggregate statistics in 2018 as the baseline. In 2018, the aggregate residential mortgage origination is \$1833.79 billion, and the total outstanding balance of the residential mortgage is \$12.32 trillion.

[23]The interest rate does not include borrower- and product-characteristic rate premiums.

To isolate the competition effect of the FHLB, I consider a second counterfactual where the FHLB still exists, but chooses to offer different prices to different banks. The prices for different banks are made so that the average funding cost of FHLB member banks is the same as in the current equilibrium, but the market structure is the same as if there was no FHLB in the first counterfactual (orange bars in Figure 17). Therefore, this counterfactual has the same cost reduction as in the current equilibrium. The only difference is the market structure in the mortgage lending, so this exercise would capture the effect of government-sponsored wholesale funding due to the shift of the industrial organization of the lending market. Figure 19 plots the offered price of FHLB advances for the three groups of banks: C_N^{FHLB} is for national banks, C_R^{FHLB} is for regional banks, and C_C^{FHLB} is for community banks.

The results show that if the FHLB were to apply this price schedule, aggregate mortgage origination would drop by 2.46%, banks' markup would rise by 3 basis points, and borrowers' welfare would drop by 3.76%. A simple back-of-the-envelope calculation implies that the FHLB's impact on the industrial organization of the mortgage market increases mortgage lending by \$50 billion and saves borrowers \$4.7 billion in interest payments every year.

10 Conclusion

In testimony before Congress, Mike Menzies, the vice chairman of the Independent Community Bankers of America (ICBA), said "the FHLBanks provide members advances for liquidity and asset/liability management... This access allows our members to offer the same home mortgage products to our customers that the largest firms offer to theirs." This paper takes an empirical approach, and illustrates that Federal Home Loan Banks are indeed playing a crucial role in supporting banks' mortgage lending. Specifically, the FHLB provides banks with low-cost wholesale funding, which eases their financial constraints, thus enabling them to lower interest rates and issue more mortgages. What is more, the flexible structure of wholesale funding improves their ability to manage interest rate risk, and enables them to offer more fixed-rate products.

More interestingly, FHLB-funded small banks have substantial spillover effects on credit markets. First, the FHLB funding shifts the market structure and makes it more competitive. As a result, the market level interest rates fall, and the aggregate mortgage lending increases significantly. The second spillover effect is on pricing efficiency. Since the small banks are better at processing local information, they are very responsive to local economic shocks. After the FHLB increases the representation of small banks, more regional risk factors are incorporated into mortgage pricing, which makes credit more efficiently allocated.

I use a structural model to quantify the macro effect of the FHLB, and find that the FHLB

increases mortgage originations by \$130 billion and saves the borrower \$13 billion in interest payments every year. The FHLB plays two roles in the economy. First, as an alternative funding source, the FHLB protects the individual banks from idiosyncratic funding shocks, and thus reduces their funding cost (the direct effect). Second, the FHLB levels the playing field for small banks, which improves market competition and facilitates the pass-through of cost reduction (the competition effect). My model enables me to quantify both effects, and show that the competition effect alone accounts for a substantial part of the overall effect. The shift of the competitive landscape of the mortgage market alone leads to an annual increase of mortgage originations of \$50 billion, and an annual decrease of \$4.7 billion in interest payments.

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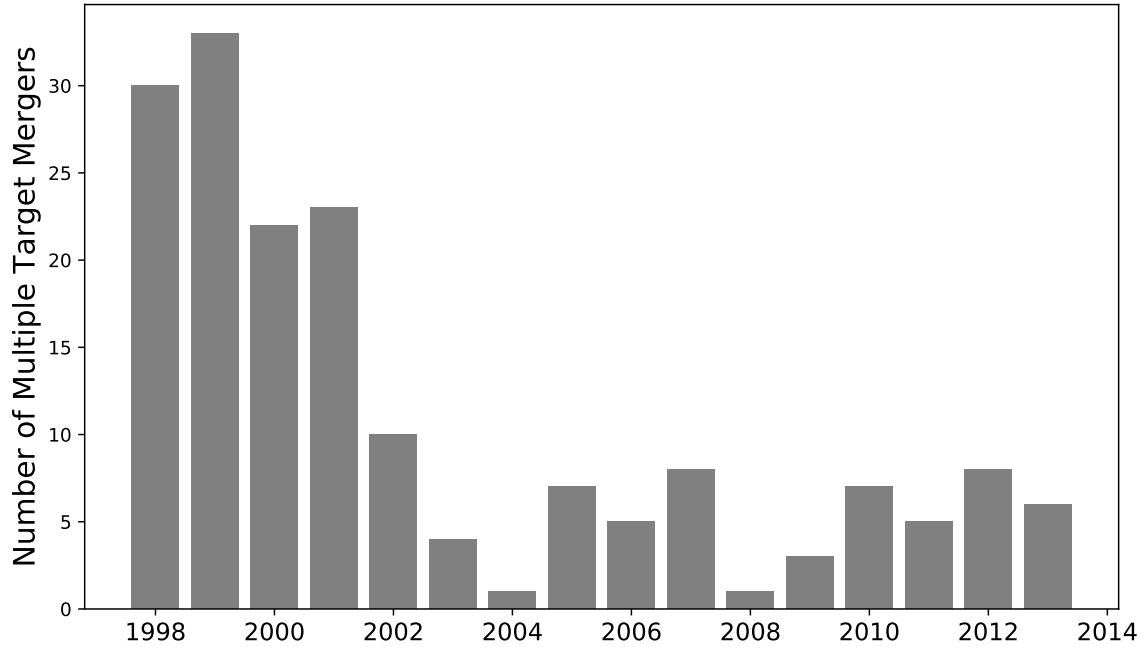Williams, Emily, 2017, Monetary Policy Transmission and the Funding Structure of Banks, *SSRN Electronic Journal* .

Figures

Figure 1   Illustration of Treated and Control Banks in an Example Merger
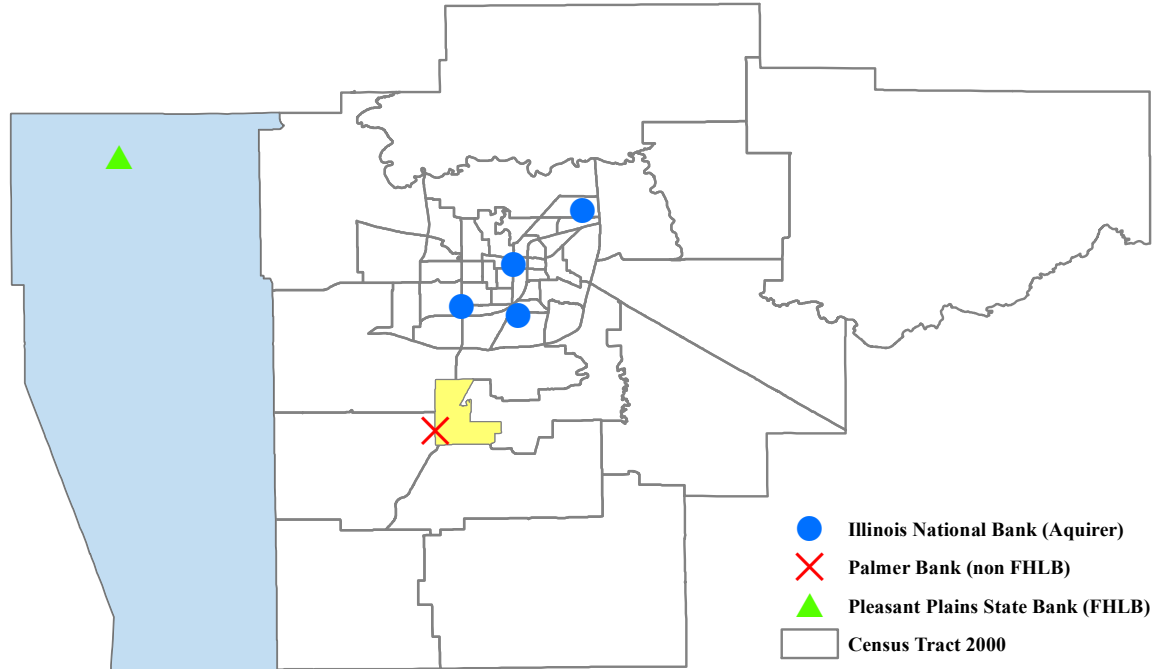
Note: This is a multiple-target merger from my sample, that serves as an example to illustrate the intuition of the identification strategy. This merger happened in 2003. The acquirer (blue dots) Illinois National Bank simultaneously merged two target banks: Palmer Bank and Pleasant Plains State Bank in the suburban area of Springfield, Illinois. The treated bank branch (cross) was not able to tap into FHLB advances before the merger, but could do so thereafter, while the control bank branch (triangle) already had FHLB access. Aside from this, both target branches experience similar organizational change due to the merger. Therefore, the within-merge difference-in-differences strategy could identify the effect of getting access to wholesale funding provided by FHLB. *Source*: FDIC, FHFA, GIS.

Figure 2　The Time Distribution of the Sample Multiple-Target Mergers

Figure 3　The Geographical Distribution of Target Branches

× 　Non FHLB Target Branches (Treated)　　▲　FHLB Target Branches (Control)
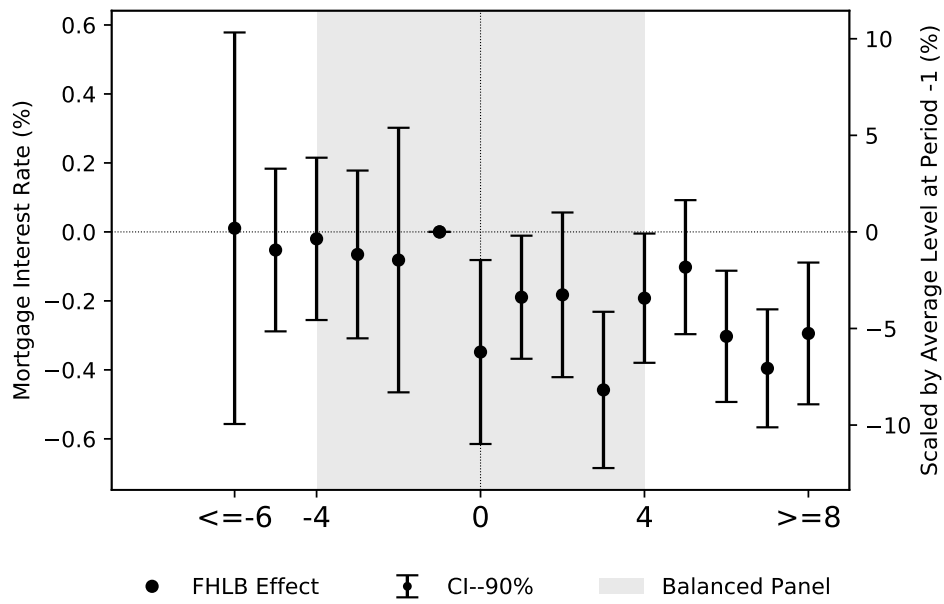
Figure 4   Effect of FHLB Funding on Mortgage Originations

Note: This figure plots the effect of FHLB funding access to lenders' mortgage originations, obtained from estimating equation (1). The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
*Source*: FDIC, FHFA, HMDA, author's own calculations.

Figure 5   Effect of FHLB Funding on Mortgage Originations of Different Business Models
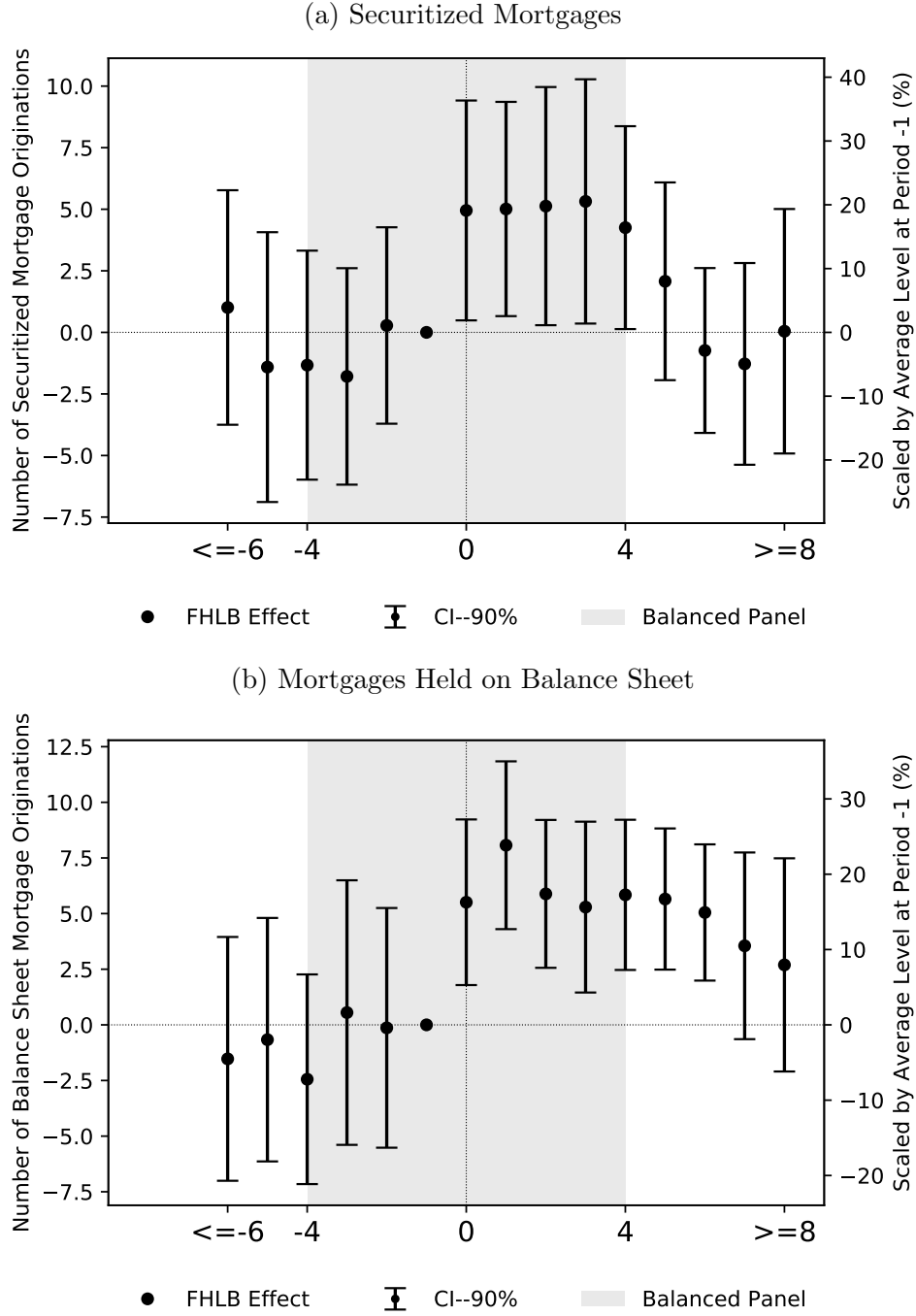
(a) Securitized Mortgages

(b) Mortgages Held on Balance Sheet

Note: This figure plots the effect of FHLB funding access to lenders' mortgage originations, obtained from estimating equation (1). Panel (a) depicts securitized mortgages, and panel (b) illustrates the mortgages that are held on banks' balance sheet. The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 6   Effect of FHLB Funding on Mortgage Interest Rate

Note: This figure plots the effect of FHLB funding access to lenders' mortgage interest rates (%), obtained from estimating equation (1). The left y-axis measures the effect in absolute mortgage rate, and the right y-axis rescales the effect by the baseline mortgage rate at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
*Source*: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 7　Effect of FHLB Funding on Mortgage Profile
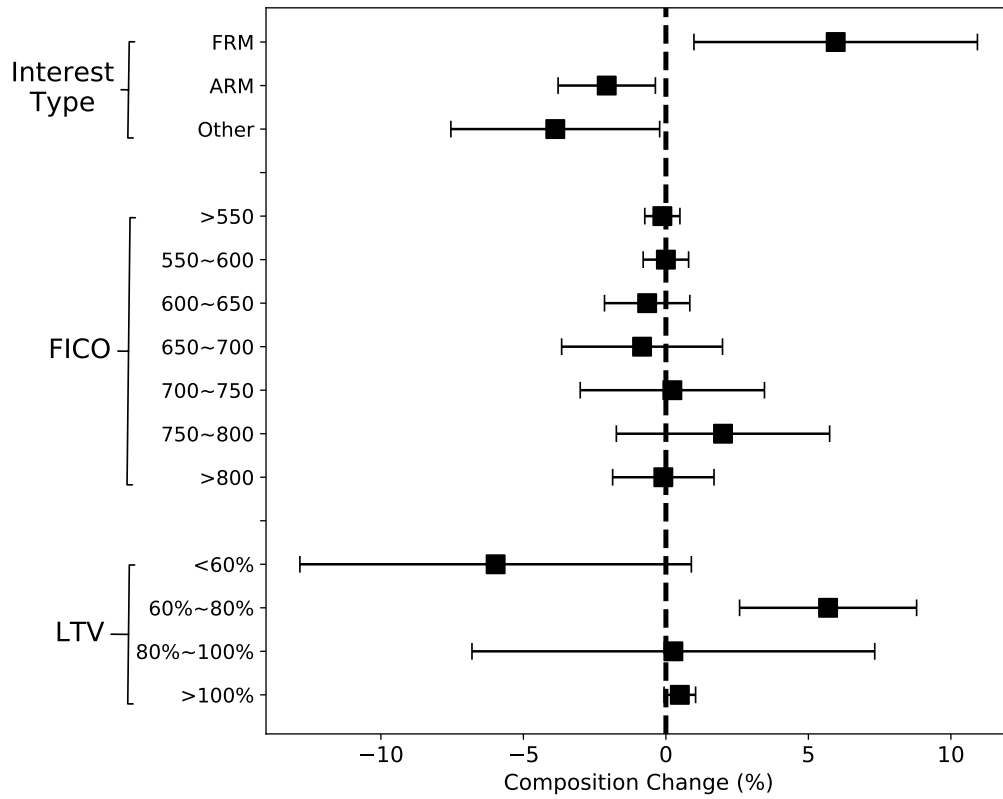
Note: This figure plots the effect of FHLB funding access to the composition change of mortgage profiles along interest type, FICO and LTV, obtained from estimating equation (2). The dependent variable is the proportion of the originating mortgages in each category. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 8   Effect on Market Concentration in the Local Census Tract

Figure 9   Effect on Aggregate Mortgage Originations in the Local Census Tract
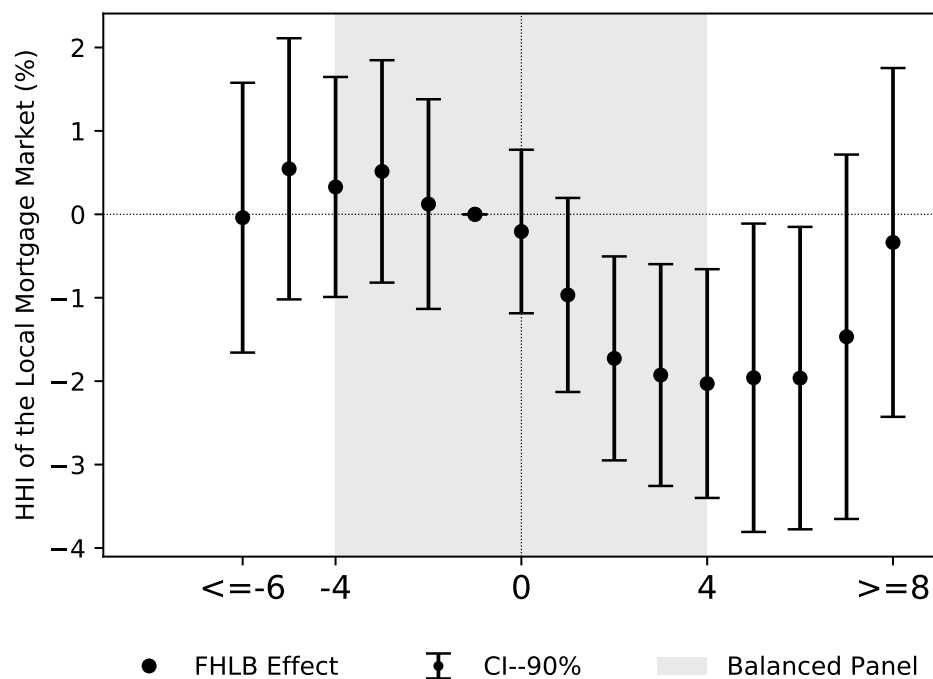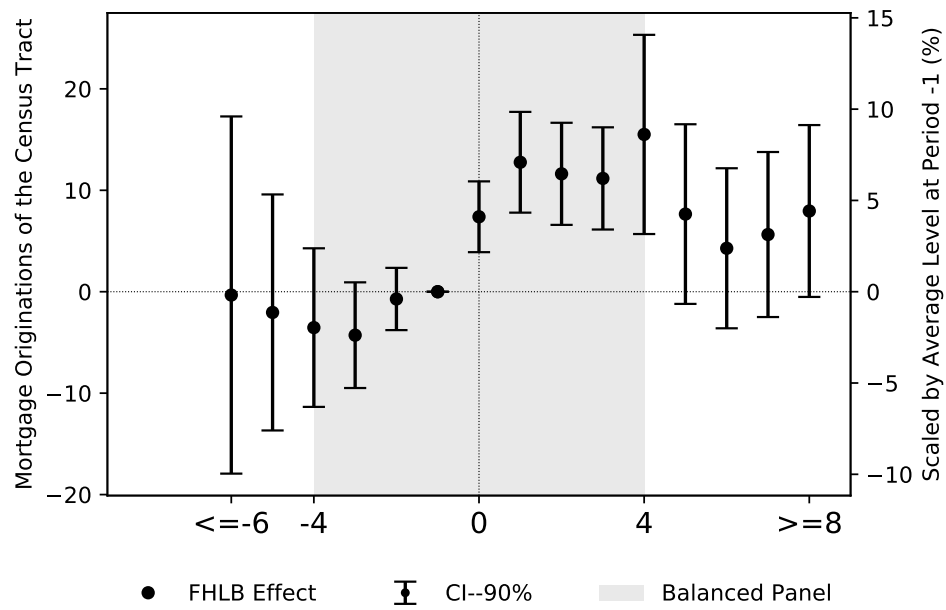
Note: This figure plots the effect to market mortgage originations after a local small bank joins FHLB, obtained from estimating equation (1).The market is defined as the 2000 census tract where the bank branch is located. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
Source: FDIC, FHFA, HMDA, author's own calculations.

Figure 10 Shift of Market Structure
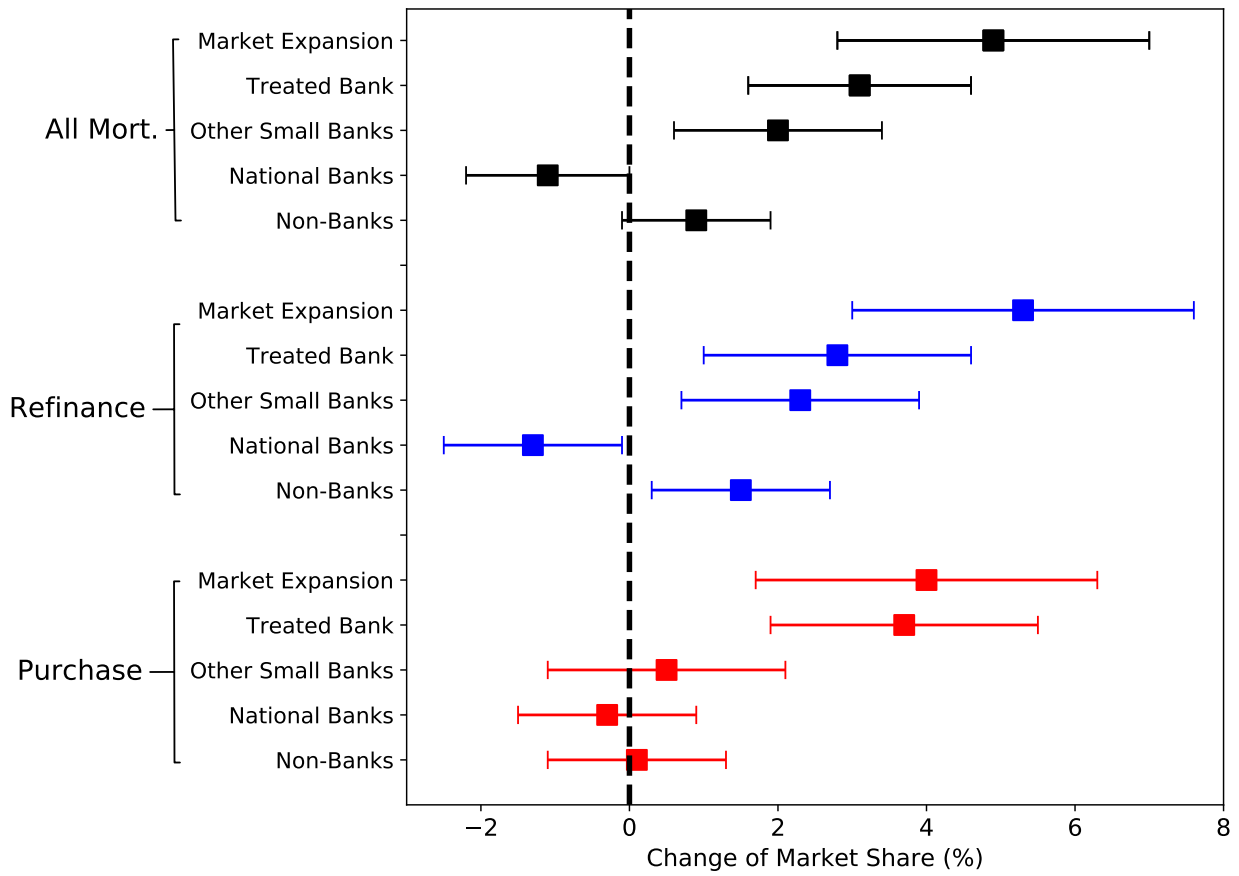
Note: This figure plots the effect of FHLB funding access to market share changes for different types of lender from estimating equation (2). The upper panel plots the effect for all mortgages. The middle panel plots the effect for refinance mortgages, and the lower panel plots the effect for purchase mortgages. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
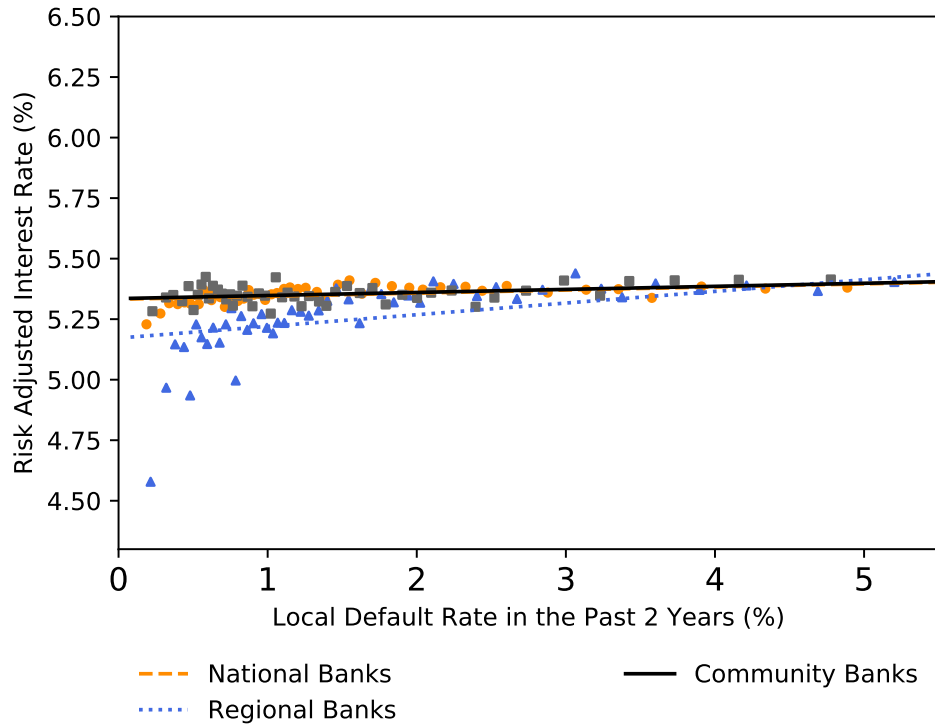*Source*: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Figure 11   Regional Pricing Schedule for Banks of Different Sizes

(a) Non-GSE Mortgage Sample
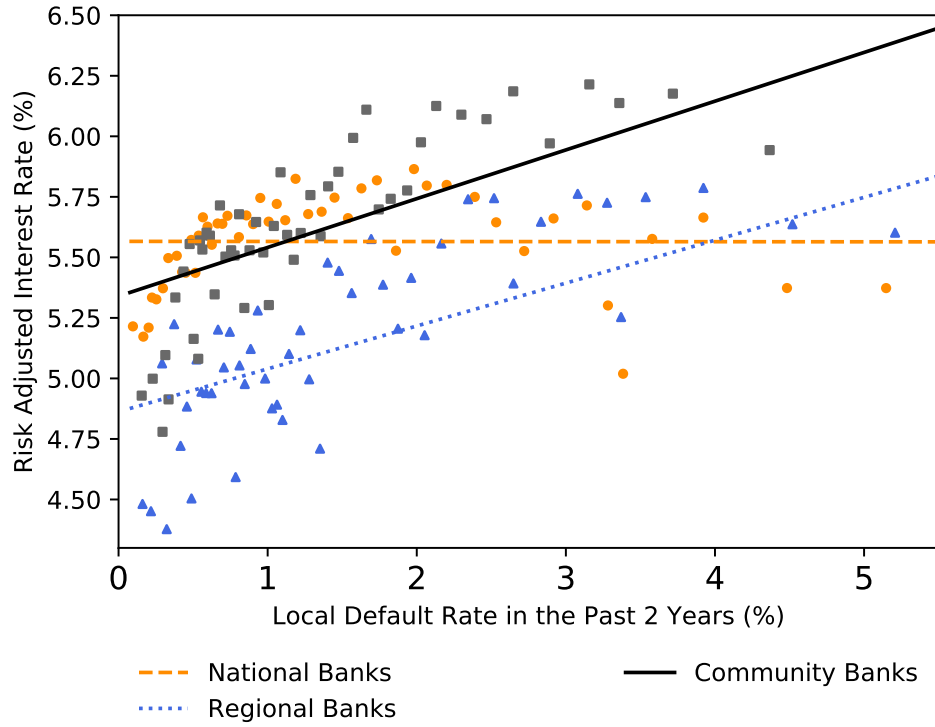
(b) GSE Mortgage Sample

Note: This figure plots the relationship between the residualized interest rate $\tilde{r}_{it}$ (y-axis) and the local lagged default rates $d_{c(i),t}$ (x-axis) for both non-GSE mortgages (panel a) and GSE mortgages (panel b). The national banks are the top 4 bank holding companies by their combined total assets. The regional banks are all banks with total assets above \$1 billion, except for the national banks. And the community banks are all banks with total assets below \$1 billion. The scatters represent the average value for 50 percentiles for each group of banks. *Source*: FDIC, FHFA, Attom, McDash, author's own calculations.

Figure 12   Concentric Rings from the Target Branch
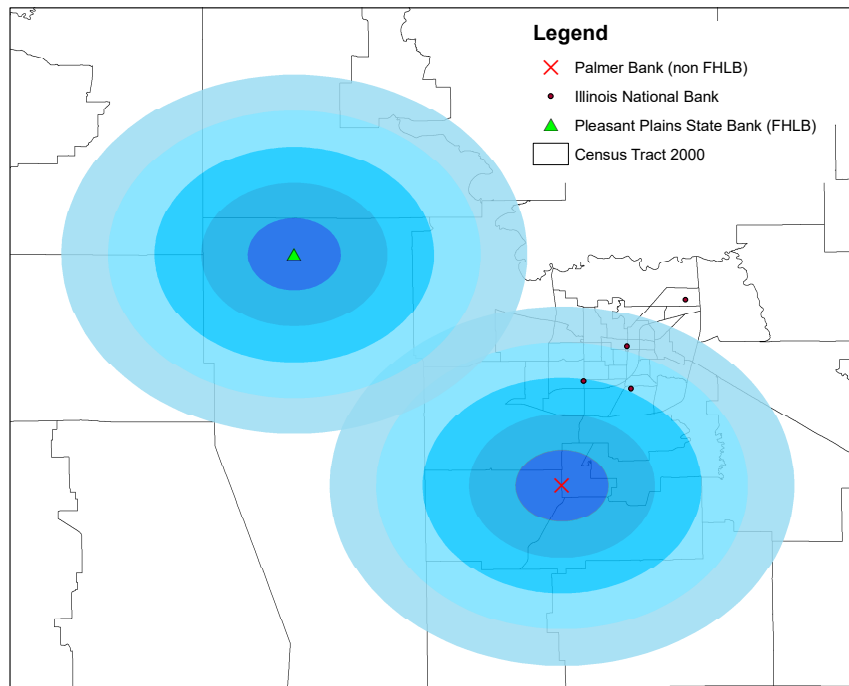
Note: This sample merger happened in 2003. The acquirer Illinois National Bank simultaneously merged two target banks: Palmer Bank and Pleasant Plains State Bank in the suburban area of Springfield, Illinois. The width of each ring belt is 2 miles.
*Source*: FDIC, FHFA, GIS.

Figure 13   FHLB Effect on Mortgage Lending Over Space
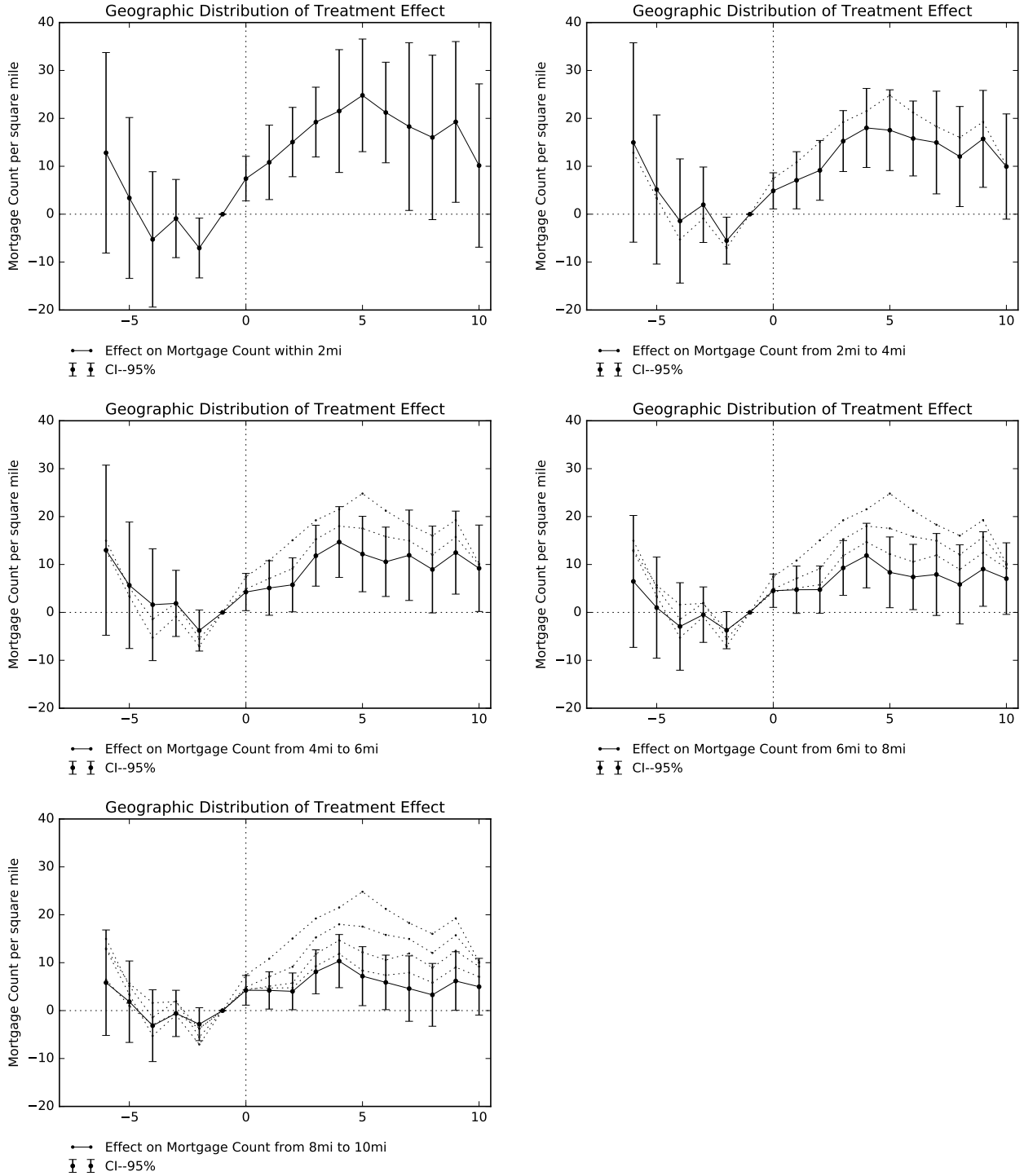
Note: This figure plots the effect on mortgage lending across different concentric rings. The results are obtained from estimating equation (1). The bars plot 95% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
*Source*: FDIC, FHFA, HMDA, McDash, author's own calculations.

Figure 14   Effect of FHLB Funding on Small Business Loan Originations
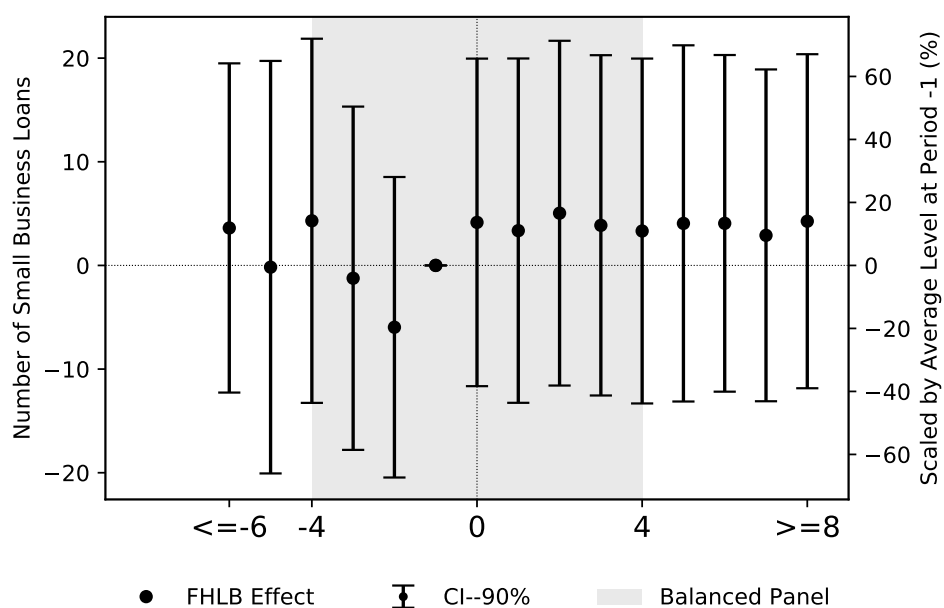
Note: This figure plots the effect of FHLB funding access to lenders' small business loan originations, obtained from estimating equation (1). The left y-axis measures the effect in absolute mortgage originations, and the right y-axis rescales the effect by the baseline mortgage originations at event year -1. The regression controls event-year fixed effect, event-branch fixed effect and county-year fixed effect. The bars plot 90% confidence intervals for each point estimate. Robust standard errors are clustered at the event level.
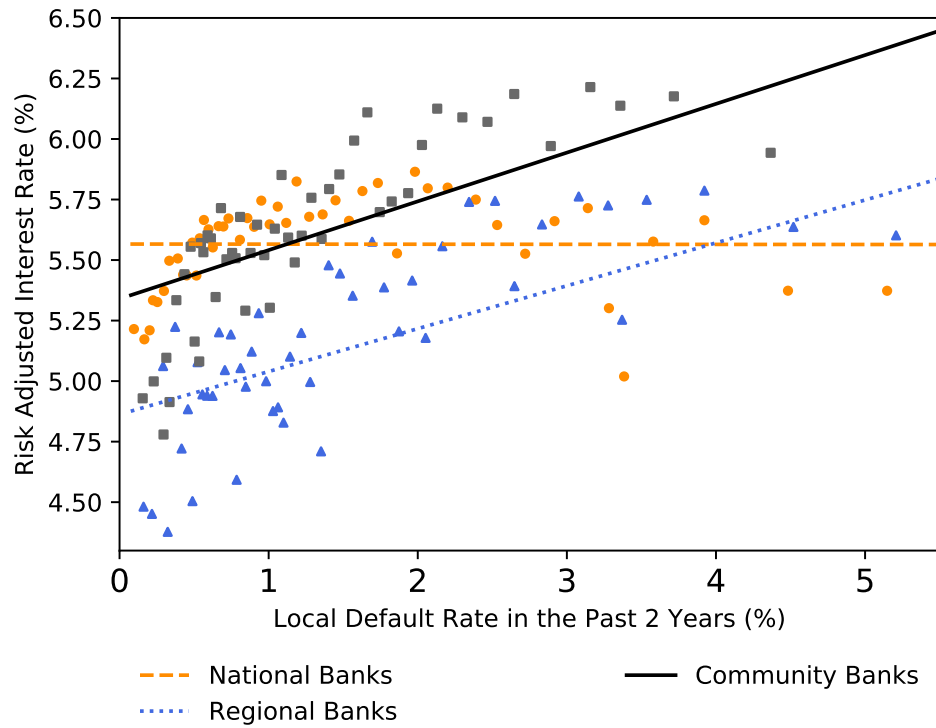*Source*: FDIC, FHFA, CRA, author's own calculations.

Figure 15   Estimates of Funding Cost
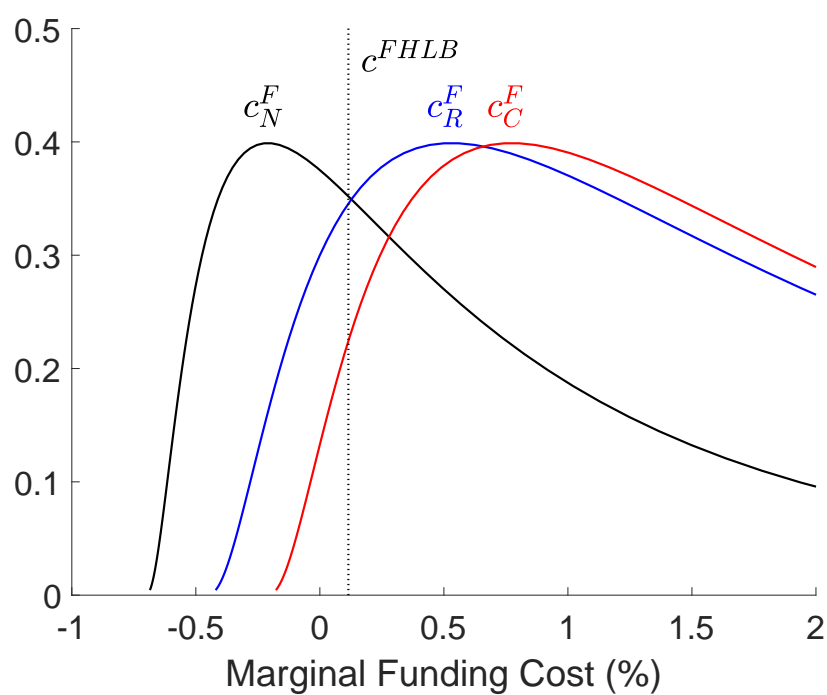
Note: This figure plots the offered price of FHLB advances for the three groups of banks: C_N^{FHLB} is for national banks, C_R^{FHLB} is for regional banks, and C_C^{FHLB} is for community banks.

Figure 16   Model Fit of Mortgage Interest Rates

(a) Empirical Interest Rates

(b) Simulated Interest Rates
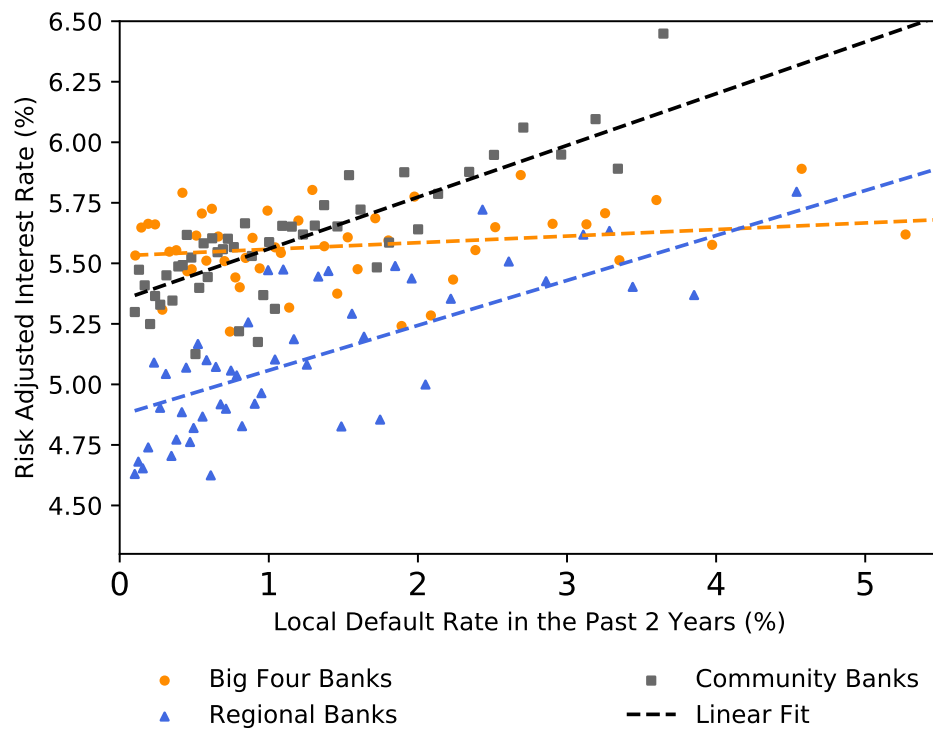
Figure 17   Counterfactual 1: Shift of Market Structure after Removing FHLB
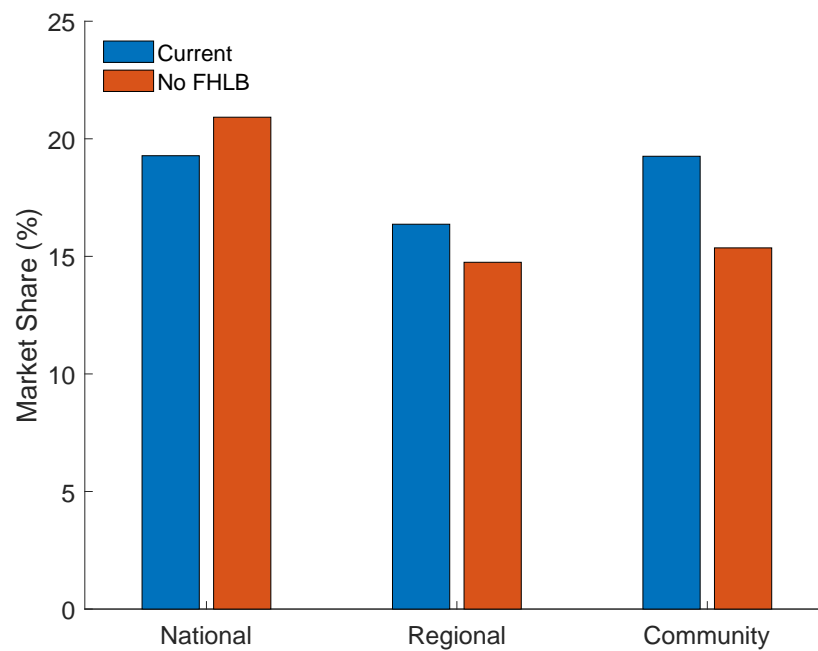
Note: This figure plots the market share of banks of different sizes for the simulated equilibrium with FHLB (blue) and the counterfactual without FHLB (orange).

Figure 18   Counterfactual 1: Average Mortgage Rates across Different Areas
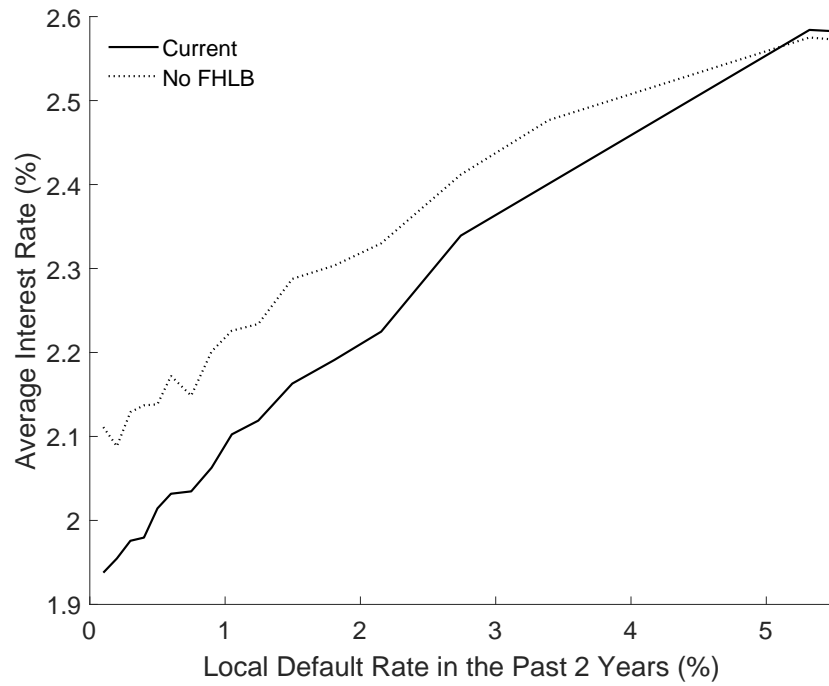
Note: This figure plots market mortgage rates across markets with different local economic conditions for the simulated equilibrium with FHLB (solid line) and the counterfactual without FHLB (dash line).

Figure 19   Counterfactual 2: FHLB Advance Price Schedule
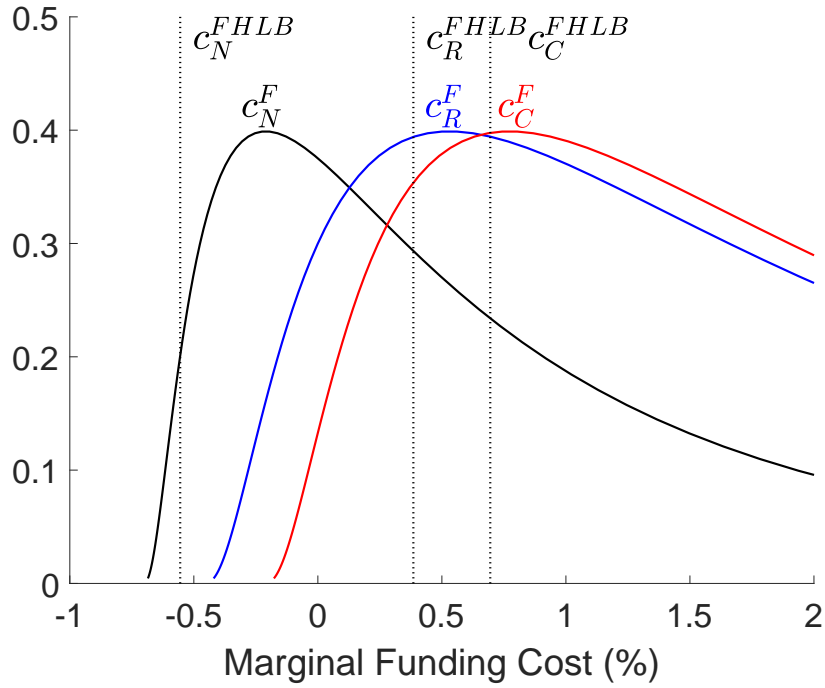
Note: This figure plots the cost of FHLB advances relative to the estimated funding cost for the three groups of banks. The black line and FHLB advance rate C_N^{FHLB} are for national banks, the blue line and C_R^{FHLB} are for regional banks, and the red line and C_C^{FHLB} are for community banks. The price schedule is made so that the average funding cost is the same as in the current equilibrium, but the market structure is the same as if there were no FHLB in the first counterfactual (orange bars in Figure 17).

Tables

Table 1   Sample Descriptive Statistics

	Non FHLB Target (1)	FHLB Target (2)	Difference within Merger (3)	p-value (4)
Panel A: Sample Size				
Multi-Target Mergers	174			
Target Banks	250	254		
Target Branches	2051	1170		
Panel B: Target Bank Characteristics Before Mergers (Unit: $Million)				
Total Asset	13,735	13,969	11,587	[0.19]
	(86,543)	(104,154)	(8,749)	
Total Deposit	9,068	9,452	5,662	[0.26]
	(58,849)	(69,608)	(5,009)	
Total Lending	7,890	8,468	5,959	[0.21]
	(47,297)	(57,534)	(4,743)	
Non-Performing Loan Ratio	0.01	0.02	-0.00	[0.86]
	(0.02)	(0.02)	(0.00)	
Loan Loss Ratio	0.02	0.02	0.00	[0.42]
	(0.01)	(0.01)	(0.00)	
Real Estate Ratio	0.60	0.65	-0.02	[0.15]
	(0.25)	(0.26)	(0.02)	
C&I Ratio	0.16	0.14	-0.00	[0.90]
	(0.11)	(0.10)	(0.01)	
Branch Count	112	114	39	[0.42]
	(589)	(602)	(49)	
Panel C: Census Tract Characteristics in 2000 Census				
Median Income	45,101	46,842	-731	[0.70]
	(20,327)	(21,454)	(1,864)	
House Unit	2,231	2,380	39	[0.64]
	(1,131)	(1,494)	(82)	
Home Ownership	0.62	0.64	-0.01	[0.36]
	(0.22)	(0.22)	(0.01)	
Minority Fraction	0.20	0.18	0.02	[0.11]
	(0.20)	(0.18)	(0.01)	
Educated Fraction	0.65	0.64	0.01	[0.58]
	(0.18)	(0.18)	(0.02)	
Mortgagor Fraction	0.69	0.69	-0.00	[0.99]
	(0.15)	(0.16)	(0.01)	
# of Bank Branches	4.32	5.02	-0.48	[0.14]
	(3.88)	(4.73)	(0.33)	

Note: This table summarizes the characteristics of the sample banks and their locating census tracts. Column (3) displays the difference within each merger event. Column (4) reports the p-value of the test that the corresponding difference is 0. Standard deviations/errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, GIS, FFIEC.

Table 2　FHLB Effect on Banks of Different Sizes

	Mortgage Originations		Mortgage Interest Rate (%)	
	(1)	(2)	(3)	(4)
FHLB	9.76***		-0.181**	
	(2.84)		(0.076)	
relative to baseline	16.3%		-3.2%	
FHLB×Regional		9.20**		-0.164**
		(3.72)		(0.079)
relative to baseline		15.2%		-2.7%
FHLB×Community		11.78***		-0.292***
		(4.23)		(0.095)
relative to baseline		20.7%		-4.3%
Event-Year FE	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓
Obs.	62,260	62,260	56,099	56,099

Note: This table reports the effect of FHLB funding access to mortgage originations and rates, obtained from estimating equation (2). Column (1) and (3) report the average effect for the full sample, while column (2) and (4) report effect for regional banks (total assets above $ 1 billion) and community banks (total assets below $ 1 billion), respectively. Below the point estimate, the row "relative to baseline" includes the size of the effect relative to the baseline of each outcome variable at event year -1. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Table 3   Effect of FHLB Funding on Market Interest Rates

Dependent Variable	Local Market	Treated Bank	Other Lenders	Other Lenders (National Banks)	Other Lenders (Small and Non-Banks)
	(1)	(2)	(3)	(4)	(5)
$FHLB$	-0.083**	-0.181**	-0.074*	-0.031	-0.093*
	(0.037)	(0.076)	(0.042)	(0.052)	(0.049)
Event-Year FE	✓	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓
Cluster	Event	Event	Event	Event	Event
Obs.	152,658	56,099	96,329	29,830	66,499

Note: This table reports the effect to the market interest rates of the mortgages after a local bank joins FHLB, obtained from estimating equation (2). Column (1) reports the effect for all lenders in the local market. Column (2) reports the effect for the treated banks, while column (3) reports the effect for lenders except for the treated banks. Column (4) illustrates the effect for national banks that are in the same market with the treated banks, column (5) focused on small banks (regional and community banks) and non-banks in the same market with the treated banks. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Table 4 Effect of FHLB Funding on Market Mortgage Rates (Triple Diff)

Dependent Variable	Market Mortgage Rates (%)				
	Safe Market	Risky Market	Full Sample	Non-GSE	GSE Loans
	(1)	(2)	(3)	(4)	(5)
Post×$FHLB$×Good Market			-0.037*	-0.048**	-0.021
			(0.019)	(0.024)	(0.016)
Post×$FHLB$	-0.096**	-0.065*	-0.061**	-0.097**	-0.028
	(0.045)	(0.038)	(0.030)	(0.041)	(0.023)
Event-Year FE	✓	✓	✓	✓	✓
Event-Branch FE	✓	✓	✓	✓	✓
County-Year FE	✓	✓	✓	✓	✓
Cluster	Event	Event	Event	Event	Event
Obs.	2,303,434	2,405,784	4,709,218	2,820,510	1,888,688

Note: This table reports the effect to the market interest rates of in both good and bad markets after a local bank joins FHLB, obtained from estimating equation (2). Column (1) and (2) still use the difference-in-differences specification, and report the effect for safe and risky markets, receptively. Markets are defined as safe if it is located in a county where the mortgage default rates in the past two years are below the national median. Column (3) further interact Post×$FHLB$ with the indicator of safe markets (triple diff). Column (4) and (5) apply the triple diff regression to GSE securitized mortgages, and non-GSE securitized mortgages receptively. The regression controls event-year fixed effect, event-branch fixed effect, county-year fixed effect, as well as a battery of variables, including tract median income, home ownership, minority fraction, educated fraction and mortgagor fraction. Standard errors in parentheses are clustered at the event level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
*Source*: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

Appendix A Appendix

A.1 Predictability of the Measure of Default Information

To gauge the predictability of such a measure of local default information, I plot the default rate of newly originated mortgages in the next 2 years against this lagged default measure in Figure A1. The observations are binned into 100 percentiles, and each dot represents the average value for each percentile. We can see that the lagged default information predicts the quality of new originations pretty strongly. Table A1 applies the linear regressions with various fixed effects. The strong predicting power of the lagged default rate is outstanding across all specifications. In terms of magnitude, the preferred specification in column (4) indicates if the default rate increased by 1% in the past two years, the likelihood of default for the current borrowers would increase by 0.53%.

Figure A1 Predicting Future Default with Lagged Default Rate
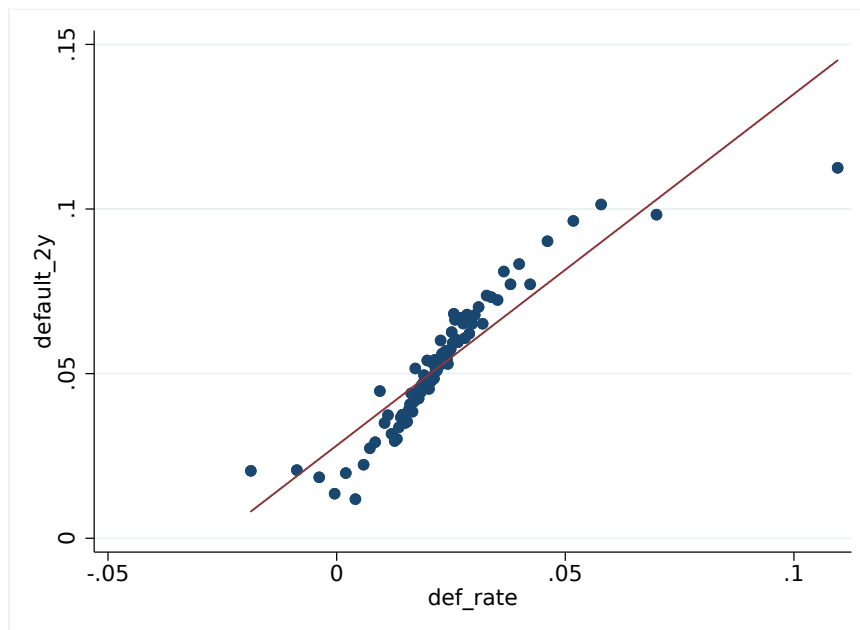
Note: This figure plots the mortgage default rate against the regional default rate in the past two years.
Source: McDash, author's own calculations.

Table A1   Predicting Future Default with Lagged Default

Dependent Variable	$d_{c,t}$			
	(1)	(2)	(3)	(4)
$d_{c,t-1}$	1.455***	1.277***	1.068***	0.534***
	(0.029)	(0.026)	(0.065)	(0.052)
County FE		✓		✓
Time FE			✓	✓
R^2	0.02	0.03	0.05	0.05
Obs.	47,596,736	47,596,720	47,596,736	475,967,20

Note: This table regress the default rate of newly originated mortgages in the next 2 years against this lagged default measure. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, McDash, author's own calculations.

A.2   Rationale for Regional Pricing

Should banks react to local past default rates? It depends on whether do local past default rates provide any useful information for banks screening process, and Table A2 reports the results of mortgage-level regressions of the mortgage default (D_{it}) on its residualized interest rate ($\tilde{r}_{it}$). Since many observable characteristics have been taken out, the residualized interest rate $\tilde{r}_{it}$ can be thought of as the soft information known by the lenders. The significant coefficient of $\tilde{r}_{it}$ across all specifications suggest the soft information is valuable in predicting the mortgage performance. What is more, if we look at its interaction with small banks in column (1), the significant positive interaction indicates the small banks' soft information has even more predicting power. Column (2) adds the past local default ($d_{c(i),t}$) into the regression. And it is strongly predicting the mortgage default. In other words, local economic conditions are informative in predicting mortgage performance, and therefore the lenders should take the local economic conditions into consideration in their screening process. More interestingly, after controlling the past local default, the small banks' pricing advantage shrinks. And this is indicating a lot of the small banks' pricing efficiency is coming from their flexibility to react to local economic shocks. Column (3) and (4) control the lender fixed effect, and present very similar pattern.

In light of this evidence, let us now consider explanations for the uniform pricing tendency of national banks. While identifying the fundamental cause of this behavior is beyond the scope of this paper, discussions and interviews with bank managers suggest two leading explanations. The first is political risk. Fair lending laws and regulations prohibit banks from treating geographies differently based on race, religion, marital status and so on. These discriminatory factors might coincidentally be correlated with local economic conditions, and regional risk based pricing might expose the lenders to

political risk and regulatory penalties. To avoid this risk, large banks might be willing to leave some money on the table and apply uniform pricing. The second is the agency problem within the bank organization. Large banks have complicated and hierarchical organization structure, which often leads to great principle-agent frictions between management and local branches (Stein, 2002). Therefore, large banks tend to give less autonomy to the local branches, and make centralized decisions. This phenomenon is more salient when decision making involves more soft information.

Table A2   The Predictability of Mortgage Default

Dependent Variable	Mortgage Default			
	(1)	(2)	(3)	(4)
$\tilde{r}_{it}$	0.788***	0.798***	0.715***	0.802***
	(0.180)	(0.282)	(0.179)	(0.226)
$\tilde{r}_{it} \times$Small	0.750**	0.485	0.663**	0.382
	(0.316)	(0.430)	(0.307)	(0.352)
Past Default		2.239***		2.559***
		(0.468)		(0.426)
Past Default×Small		1.584**		1.363**
		(0.671)		(0.637)
Lender FE			✓	✓
$\bar{y}(\%)$	6.40	6.40	6.40	6.40
Obs	4,748,419	4,748,419	4,747,735	4,747,735

Note: This table reports the results of mortgage-level regressions of mortgage default on its residualized default rate. Mortgage is defined as default if it is at least 2 month delinquent in the first 2 years after origination. The residualized interest rate $\tilde{r}_{it}$ is the residual from regression 3. A bank is small if it is either a regional or community bank The unit of both independent and dependent variables is percentage. Standard errors in parentheses are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: FDIC, FHFA, HMDA, Attom, McDash, author's own calculations.

A.3   Micro Foundation: Moral Hazard of Branch Manager (Costly State Verification Framework)

In this part, I provide a micro foundation for the assumption that a lender's perception of local economic conditions is a function of the lender's size in subsection 7.1.3. This micro foundation builds on the agency frictions between the lender management and local branch managers, a la Stein (2002), and attributes national banks' low responsiveness to local shocks to their great cost in verifying local branch managers' report on local default prediction.

For a bank b with a branch network $\{b_j\}_{j=1}^{N(b)}$, each of its branch b_j recoups interest income from mortgage lending in market $M(b_j)$, and incur cost from funding the mortgages and other operational

expenses. The (expected) profit can be written as:

$$\max_{r_{b_j,M(b_j),t}} \pi_{b_j,M(b_j),t} = I_{M(b_j)} S_{b_j,M(b_j),t} \bar{Q} \bar{T} \left[(r_{b_j,M(b_j),t} - c_{b_j,M(b_j),t}) - \bar{l} E_b[d_{M(b_j),t}] \right] \qquad \text{(A1)}$$

where $S_{b_j,M(b_j),t}$ is the market share of bank branch b_j its market $M(b_j)$ at period t.

For simplicity, I assume there is no heterogeneity in household disutility coefficients ($\alpha_i = \alpha$). Solving the first order condition for problem (A1), we get the optimal interest rate at the branch level

$$r_{b_j,t} - \frac{1}{\alpha[1 - S_{b_j,M(b_j),t}(r_{b_j,t})]} = c_{b_j,t} + \bar{l} E \left[d_{M(b_j),t} \Big| \mathcal{I}_{M(b_j),t} \right], \qquad \text{(A2)}$$

which implies the interest rate policy function

$$r_{b_j,t} = R \left(E \left[d_{M(b_j),t} \Big| \mathcal{I}_{M(b_j),t} \right] \right) \qquad \text{(A3)}$$

Figure A2   Interest Rate Policy Function
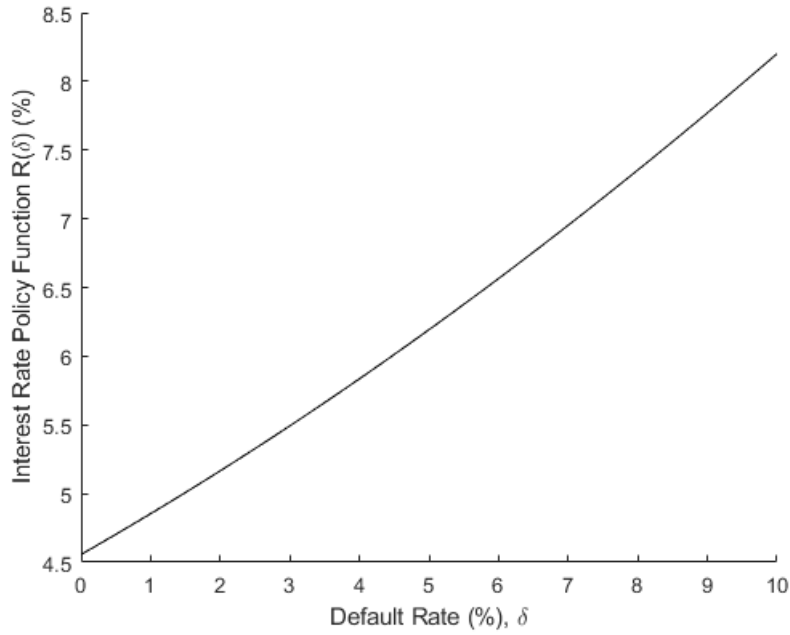
Since the left hand side of equation (A2) is increasing with $r_{b_j,t}$ and the right hand side is increasing with $E \left[d_{M(b_j),t} \Big| \mathcal{I}_{M(b_j),t} \right]$, we can conclude $R(\cdot)$ is an increasing function as illustrate by Figure A2.

A.3.1   Branch Manager's Problem

The local branch manager can observe the local economic condition with some noise

$$\hat{\delta}_{b_j,M(b_j),t} = \delta_{M(b_j),t} + \epsilon_{\delta,t}, \tag{A4}$$

$$\begin{bmatrix} \delta_{M(b_j),t} \\ \epsilon_{\delta,t} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \bar{\delta} \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{\delta}^2 & 0 \\ 0 & \sigma_{\epsilon_{\delta}}^2 \end{bmatrix} \right)$$

and would report to the central management for rate setting. She will choose the optimal level of report $\tilde{\delta}_{b_j,M(b_j),t}$ to maximize her utility.

$$\max_{\tilde{\delta}_{b_j,M(b_j),t}} u_{b_j,t} = E\left[u(S_{b_j,M(b_j),t}) | \hat{\delta}_{b_j,M(b_j),t}, \tilde{\delta}_{b_j,M(b_j),t} \right]$$

Following Stein (2002), I assume the branch manager's utility depends on her total market share in the local market, which can be motivated by the manager's private benefits of control that are proportional to gross lending. The function $u(\cdot)$ transform the branch's market share to the manager's utility, and $u'(\cdot) > 0$. Since the market share is a decreasing function with interest rate, and thus expected default rate, the local manager has an incentive to underreport the local default prediction $(\tilde{\delta}_{b_j,M(b_j),t} \leq \hat{\delta}_{b_j,M(b_j),t})$.

A.3.2   Bank Central Management's Problem

To prevent the local branch manager from underreporting, the central management of the bank could audit the local branch and get to know the realization of $\delta_{M(b_j),t}$ at a cost of A. And the central management should decide under what condition they would carry out the audit, and how they set the interest rate according to their available information. With this moral hazard issue, the central management's profit maximization problem becomes

$$\max_{r_{b_j,t},a_{b_j,t}} \pi_{b_j,M(b_j),t} = E\left[I_{M(b_j)} \bar{Q} \bar{T} S_{b_j,M(b_j),t} \left[(r_{b_j,t} - c_{b_j,t}) - \bar{l} d_{M(b_j),t} \right] - A a_{b_j,t} \,\middle|\, \mathcal{I}_{M(b_j),t} \right] \tag{A1$'$}$$

$$s.t. \quad \mathcal{I}_{M(b_j),t} = \begin{cases} \{\tilde{\delta}_{b_j,M(b_j),t}\} & \text{if } a_{b_j,t} = 0 \\ \{\tilde{\delta}_{b_j,M(b_j),t}, \delta_{M(b_j),t}\} & \text{if } a_{b_j,t} = 1 \end{cases}$$

A.3.3   Optimal Contract with Costly State Verification

Following Townsend (1979), this paper focuses on the contract space with deterministic audit. In another word, the decision whether the central management audits the local branch is deterministic conditional on the reported default prediction $\tilde{\delta}_{b_j,M(b_j),t}$.

Theorem 1. *Under the deterministic audit assumption, the optimal contract is specified only by two parameters δ^c and r^c. And the optimal contract is*
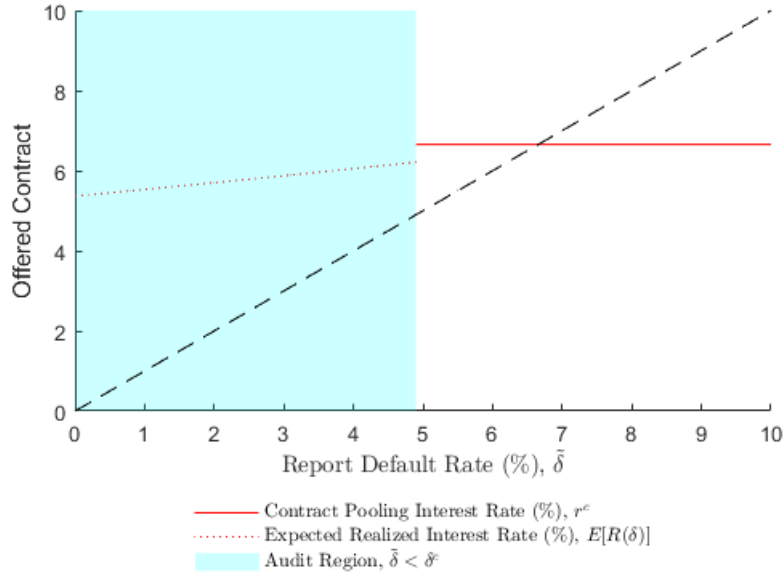
$$a_{b_j,t} = \begin{cases} 0 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ 1 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

$$r_{b_j,t} = \begin{cases} r^c & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ R(\delta_{M(b_j),t}) & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

And the branch manager always (weekly) prefers to report his observed default signal truthfully

$$\tilde{\delta}_{b_j,M(b_j),t} = \hat{\delta}_{b_j,M(b_j),t}.$$

Figure A3   Optimal Contract

Proof. The general principle in the contract theory implies any optimal equilibrium can be achieved by a truth revealing contract. Without loss of generality, we focus on the truth revealing contract space.

First, we can show $r_{b_j,t}(\tilde{\delta}_{b_j,M(b_j),t})$ is a uniform function ($r_{b_j,t} = r^c$) in the non-audit region, by contradiction. Let $\mathcal{R}^{\text{audit}}$ denote the audit region. Assuming the opposite, there exist $\tilde{\delta}_1 \neq \tilde{\delta}_2$ in

$\mathcal{R}/\mathcal{R}^{\text{audit}}$, so that $r_{b_j,t}(\tilde{\delta}_1) > r_{b_j,t}(\tilde{\delta}_2)$. Then

$$E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right]$$

$$=u(S_{b_j,M(b_j),t}(r_{b_j,t}(\tilde{\delta}_1)))$$

$$<u(S_{b_j,M(b_j),t}(r_{b_j,t}(\tilde{\delta}_2)))$$

$$=E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right]$$

Such a contract is not truth revealing, since the branch manager will report $\tilde{\delta}_2$ if she observes $\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1$. This leads to a contradiction.

Second, we can prove $r_{b_j,t} = R(\delta_{M(b_j),t})$ in the audit region $\mathcal{R}^{\text{audit}}$. Conditional on auditing, the management's profit maximization problem becomes

$$\max_{r_{b_j,t}} \pi_{b_j,M(b_j),t} = I_{M(b_j)}\bar{Q}\bar{T}S_{b_j,M(b_j),t}\left[(r_{b_j,t} - c_{b_j,t}) - \bar{l}E\left[d_{M(b_j),t}\,\middle|\,\delta_{M(b_j),t}\right]\right] - A$$

so $r_{b_j,t} = R(\delta_{M(b_j),t})$, by the definition of $R(\cdot)$.

Third, let us prove $\mathcal{R}^{\text{audit}} = \{\tilde{\delta} : \tilde{\delta} < \delta^c\}$. If not, there exist $\tilde{\delta}_1 < \tilde{\delta}_2$, so that $a_{b_j,t}(\tilde{\delta}_1) = 0, a_{b_j,t}(\tilde{\delta}_2) = 1$.

$$E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right] \qquad \text{(observe } \tilde{\delta}_1, \text{ report } \tilde{\delta}_2\text{)}$$

$$=E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1\right]$$

$$>E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_2\right]$$

$$=E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_2, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_2\right] \qquad \text{(observe } \tilde{\delta}_2, \text{ report truthfully)}$$

$$\geq E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_2, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] \qquad \text{(observe } \tilde{\delta}_2, \text{ report } \tilde{\delta}_1\text{)}$$

$$=E\left[u(S_{b_j,M(b_j),t})|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1, \tilde{\delta}_{b_j,M(b_j),t} = \tilde{\delta}_1\right] \qquad \text{(observe } \tilde{\delta}_1, \text{ report truthfully)}$$

Again, such a contract is not truth revealing, since the branch manager will report $\tilde{\delta}_2$ to trigger auditing if she observes $\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \tilde{\delta}_1$. This leads to a contradiction. $\qquad\square$

Then let us investigate the quantitative restriction for the two parameters (δ^c, r^c) that specify the optimal contract.

Theorem 2. *The optimal contract (δ^c, r^c) have to satisfy*

$$u(S_{b_j,M(b_j),t}(r^c)) = E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\tilde{\delta}}_{b_j,M(b_j),t} = \delta^c\right]. \tag{A5}$$

and $r^c(\delta^c)$ is an increasing function.

Equation A5 makes the branch manager indifferent between auditing and taking the pooling rate r^c without auditing.

Proof. Since $a_{b_j,t}(\delta^c) = 0$, it implies

$$u(S_{b_j,M(b_j),t}(r^c)) \geq E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right].$$

Suppose

$$u(S_{b_j,M(b_j),t}(r^c)) > E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right].$$

The continuity of functions $u(\cdot)$, $S(\cdot)$ and $R(\cdot)$, as well as the normality of the distributions implies there exists $\delta' < \delta^c$, so that

$$E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta^c\right] < E\left[u(S_{b_j,M(b_j),t}(R(\delta_{M(b_j),t})))|\hat{\delta}_{b_j,M(b_j),t} = \delta'\right]$$

$$< u(S_{b_j,M(b_j),t}(r^c))$$

which implies it is better to report $\tilde{\delta}_{b_j,M(b_j),t} = \delta^c$ if the branch manager observes $\hat{\delta}_{b_j,M(b_j),t} = \delta'$, which contracts the truth revealing principle of the contract.

Since the left hand side of the equation A5 is decreasing with r^c, and right hand side is decreasing with δ^c, $r^c(\delta^c)$ is thus an increasing function. □

A.3.4 Equilibrium Outcomes

Under the optimal contract, the bank management needs to determine the contract $(\delta^c, r^c(\delta^c))$ before any signal is observed by the branch managers.

$$\max_{\delta^c} \pi_{b_j,M(b_j),t} = E\left[I_{M(b_j)}\bar{Q}\bar{T}S_{b_j,M(b_j),t}\left[(r_{b_j,t} - c_{b_j,t}) - \bar{l}d_{M(b_j),t}\right] - Aa_{b_j,t}\right] \tag{A1''}$$

$$s.t. \quad a_{b_j,t} = \begin{cases} 0 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ 1 & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

$$r_{b_j,t} = \begin{cases} r^c(\delta^c) & \text{if } \tilde{\delta}_{b_j,M(b_j),t} \geq \delta^c \\ R(\delta_{M(b_j),t}) & \text{if } \tilde{\delta}_{b_j,M(b_j),t} < \delta^c \end{cases}$$

$$\tilde{\delta}_{b_j,M(b_j),t} = \hat{\delta}_{b_j,M(b_j),t} = \delta_{M(b_j),t} + \epsilon_{\delta,t}$$

Problem A1″ is an ex ante optimization problem, and would pin down the cutoff default rate δ^c, and therefore the optimal contract.

Specifically, we can show δ^c is decreasing with the cost parameter A. The more costly it is to verify the state, the less likely the local branch is audited, and the more pooling the equilibrium
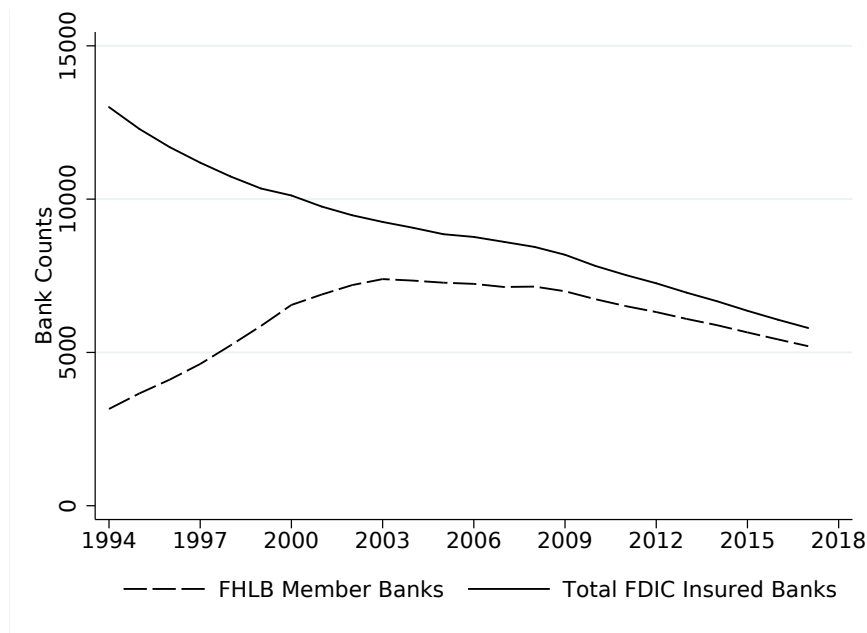
features.

Once the optimal contract is determined, we can calculate all equilibrium outcomes. In this paper, we are specially interested in the (expected) interest rates conditional on the local realized default rate $E[r_{b_j,t}|\delta_{M(b_j),t}]$.

Figure A4 Equilibrium Interest Rate
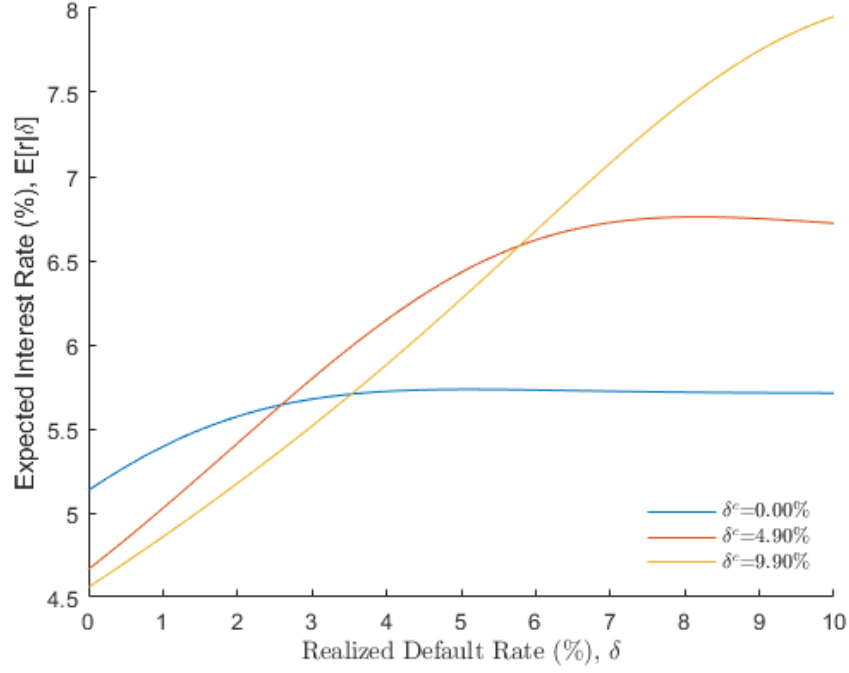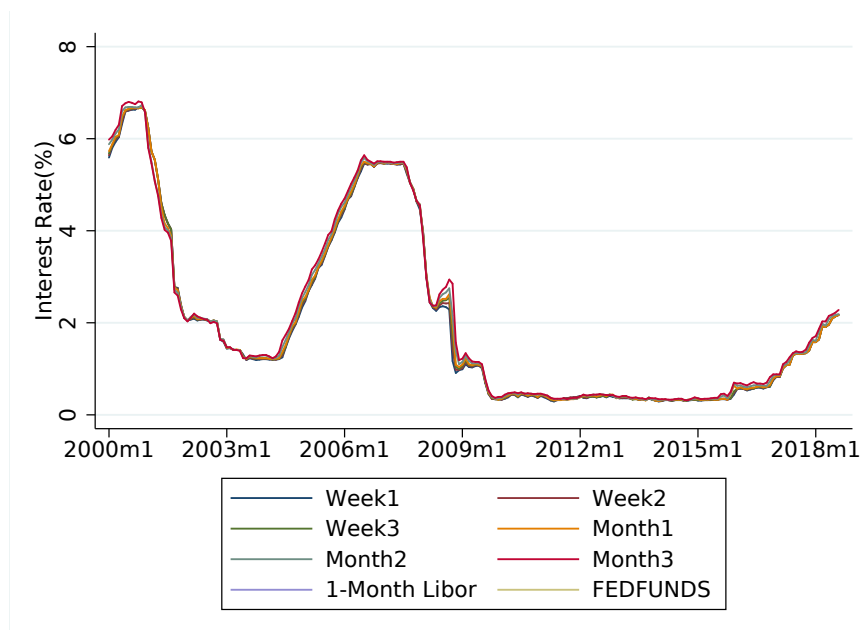
Appendix B   Additional Figures

Figure B1   Historical Trend of FHLB Members

Note: This figure plots the time series of the number of all FDIC insured banks (solid line) and FHLB member banks.
Source: FDIC, FHLB.

Figure B2   Historical Advances Rates from FHLB Des Moines

Note: This figure illustrates the historical advance rates of various maturities from an FHLB (Des Moines).
Source: FHLB of Des Moines.

Appendix C   Additional Tables

Table C1   Residualize Interest Rates Regressions

Dependent Variable	Mortgage Interest Rates			
	(1)	(2)	(3)	(4)
Quarter FE	✓	✓	✓	✓
FICO	✓	✓	✓	✓
LTV		✓	✓	✓
Lien Status				✓
Interest Type				✓
Loan Purpose				✓
Winsorsize			✓	✓
R^2	0.55	0.60	0.68	0.71
Obs.	43,385,108	43,190,260	41,009,706	41,009,706

Note: The regressions in this table residualize the mortage rates with variable specifications. Specification (4) is the preferred one. Winsorsizing is executed at the 1% level.
Source: FDIC, FHFA, GIS.