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The Geographic Flow of Bank Funding and Access to Credit: Branch Networks, Local Synergies, and Competition

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The Geographic Flow of Bank Funding and Access to Credit: Branch Networks, Local Synergies and Competition*

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Abstract

Geographic dispersion of depositors, borrowers, and banks may prevent funding from flowing to areas of high loan demand, limiting credit access. We provide evidence of geographic imbalance of deposits and loans, and develop a methodology for investigating the contribution to this imbalance of (i) branch networks, (ii) market power, and (iii) scope economies, using US bank-county-year level data. Results are based on a novel measure of deposits and loans imbalance, and estimation of a structural model of bank competition that admits interconnections across locations and between deposit and loan markets, thereby permitting counterfactuals highlighting the role of the three factors.

Keywords: Geographic flow of bank funds; Access to credit; Bank oligopoly competition; Branch networks; Economies of scope between deposits and loans.

JEL codes: L13, L51, G21

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1 Introduction

An important determinant of credit provision is the availability of deposits (Jayaratne and Morgan, 2000; Ben-David, Palvia, and Spatt, 2017). However, in any given region, the demand for loans may not always coincide with the availability of deposits. Geographic frictions, such as asymmetric information and transaction costs, limit the flow of funds across regions such that there can arise substantial geographic imbalances in access to credit and possibly even *credit deserts*. In turn, limited access to credit can impact entrepreneurship levels, employment, wages, and economic growth (see for instance Gine and Townsend (2004)).

Wholesale liquidity markets could help address these imbalances. Banks can buy and sell liquidity (deposits) in the interbank wholesale market. However, transaction costs arise due to bank precautionary motives and liquidity hoarding (Ashcraft el al., 2011; Acharya and Merrouche, 2012). Alternatively, banks may be able to use their branch networks to overcome geographic frictions and move liquidity from one region to another, and transaction costs are likely to be smaller than those incurred using the interbank market (Coase, 1937). However, two counterbalancing forces can affect negatively the willingness of a bank to transfer funds between its branches: (i) economies of scope and other synergies between deposits and loans at the branch level, and (ii) local market power. Economies of scope may arise because clients prefer to have their deposit account and their mortgage in the same bank, or because a bank's cost of managing a deposit account and a loan may be smaller if they belong to the same client.[1] These and other synergies create incentives to concentrate lending activity in branches with high levels of deposits, and therefore to limit the geographic flow of liquidity to markets with more need of credit.[2] Local market power too can have a negative impact on the geographic flow of credit. Increased market power implies that a change in the marginal cost of loans (e.g., a reduction in the interbank interest rate) is only partially passed-through to borrowers. As a result, smaller markets with highly concentrated market structures may not benefit from increases in the supply of credit as much as more competitive markets.[3]

[1] See for instance Kashyap, Rajan, and Stein (2002), Mester, Nakamura, and Renault (2006), Norden and Weber (2010), and Egan, Lewellen, and Sunderam (2017).

[2] There are factors other than economies of scope that can generate synergies between deposits and loans at the branch or local market level. For instance, the Community Reinvestment Act (CRA) introduces incentives for banks to use local deposits to fund local loans. In this paper, we are not concerned with identifying the specific sources of synergies, either economies of scope or others. We are interested in studying how these synergies affect the geographic imbalances between deposits and loans.

[3] Black and Strahan (2002) and Cetorelli and Strahan (2006) provide empirical evidence of how entrepreneurs and potential entrants in nonfinancial sectors face more difficult access to credit in local markets

The purpose of this paper is to provide systematic evidence on the extent to which deposits and loans are geographically imbalanced in the US commercial banking industry, and to investigate empirically the contribution of branch networks, economies of scope, and local market power to this imbalance. To perform our analysis we assemble a dataset from the US banking industry for the period 1998-2010. We merge data at the bank-county-year level from two sources. Deposit and branch-network information are collected from the *Summary of Deposit* (SOD) data provided by the *Federal Deposit Insurance Corporation* (FDIC). Information on lending comes from the *Home Mortgage Disclosure Act* (HMDA) data set, which provides detailed information on mortgage loans.

To measure the imbalance of deposits and loans we adapt techniques developed in sociology and labour economics to quantify residential segregation. These measures capture the extent to which individuals from different social groups live together or apart within a given geographical area (Jahn, Schmid, and Schrag, 1947; Duncan and Duncan, 1955; Atkinson, 1970; White, 1983 and 1986; and Cutler et al., 1999).[4] We develop an index of the imbalance between deposits and loans to capture the degree to which a bank transfers funds between geographic locations. Our findings suggest that, while there are some banks that transfer funds between geographic locations, the majority of banks exhibit a strong home bias. Furthermore, we find evidence that some regions of the country have much larger shares of total deposits than they do of loans, implying an important amount of segregation.

To investigate the factors that contribute to the geographic imbalance of deposits and loans requires a model that allows for interconnections across geographic locations and between deposit and loan markets such that local shocks to deposits or loans can affect endogenously the volume of loans and deposits in every local market. The main contribution of this paper is to develop and estimate a structural model of bank oligopoly competition for *both* deposits and loans in multiple geographic markets allowing for rich interconnections. We characterize an equilibrium of this multimarket oligopoly model and propose an algorithm to solve for it. Our approach allows us to perform counterfactual experiments that provide evidence of the effect of branch networks, economies of scope, local market power, and various public policies on the geographic diffusion of funds.

In our model, differentiated banks sell deposit and loan products in multiple local markets (counties). The model incorporates three variables, which may affect demand and costs of

characterized by a concentrated banking sector.

[4] More recently, they have been used by Gentzkow et al. (2019) to quantify the degree of polarization in political speech in the US.

loans and deposits in a local market. First, is the number of branches the bank has in the local market. Having more branches may affect the marginal cost of managing deposits and loans and/or generate consumer awareness and willingness to pay. Second, is the total amount of deposits the bank has at the national level, which may reduce the bank's risk for liquidity shortage and the need to borrow at interbank wholesale markets. This introduces an important interconnection between local markets in a bank's operation. The final factor is the amount of deposits (loans) the bank has in the local market, which may increase consumer demand for loans (deposits) and/or reduce the bank's marginal cost of loans (deposits) due to economies of scope in managing deposits and loans. The resulting structure bears resemblance to models of two-sided markets (see for instance Rysman (2004) and Fan (2013)).

The structural parameters associated with these three variables are fundamental for the predictions of the model. Estimation must address endogeneity and simultaneity of the number of branches and of local and total deposits and loans. Our identification approach involves controlling for a rich fixed-effects specification of the unobservables, that includes fixed effects at the bank-county, year, and county-year levels. We show that under reasonable assumptions we can obtain difference-in-difference transformations of the structural equations of the model such that in these transformed equations we can use as instrumental variables the lagged number of branches of a bank in a county, lagged deposits, loans, and number of branches of competing banks in the county, and the socioeconomic conditions in geographically distant counties where the bank has branches. We use these moment conditions to obtain a GMM estimator of the structural parameters of the model.

Estimation yields the following results. First, the number of branches in a county increases (reduces) substantially the demand for (cost of) both deposits and loans, though the effect is significantly smaller for loans. Second, we find evidence of substantial economies of scope between deposits and loans at the bank and local-market level. Third, the effect of a bank's total deposits on demand for (cost of) loans is positive (negative) and significant both economically and statistically, which implies that banks' internal liquidity reduces the cost of lending.

Our structural approach allows us to evaluate factual and counterfactual policies that affect the flow of funding to those markets where deposits are scarce. We consider the following counterfactual experiments. First, we look at the contribution of branch networks to the geographic flow of credit by imposing the restriction that banks only operate in one state. This experiment tries to evaluate the effect on the geographic imbalance of deposits of a regulation that prohibits banks from operating branch networks in multiple states, as was the case prior to the Riegle-Neal Act of 1994. We implement this counterfactual by dividing every multi-state bank in our sample into different independent banks, one for each state. Second, we study the effects of eliminating economies of scope between deposits and loans. Third, we look at the effect of eliminating county heterogeneity in local market power by imposing the restriction that every county has two banks in the deposit market and eight in the loans market (i.e. the median values in our sample). Finally, we study the potential *geographic non-neutrality* of different government policies. We evaluate how a (counterfactual) tax on deposits, the likes of which have been implemented in a number of jurisdictions, would affect the provision of credit and, more interestingly, its geographic distribution. We also investigate to what extent national aggregate shocks (e.g., business cycle, monetary policy) affect bank credit in a geographically non-neutral way.

Our findings suggest that multi-state branch networks contribute significantly to the geographic flow of credit, but benefit mostly larger/richer counties. On the other hand, local market power has a substantial negative effect on the geographic flow of credit. Limited competition in small and medium size counties plays an important role in limiting the amount of credit received by these counties. Economies of scope are found to play a smaller role. Our results also suggest that neither a deposit tax nor a national shock would be geographically neutral in their effect of bank credit.

Our model builds on and extends the literature on structural models of bank competition. Previous work has looked separately at either the loan or deposit sides of the market. Corbae and D'Erasmo (2013, 2019), Benetton (2018) and Crawford, Pavanini, and Schivardi (2018) all focus on the loan side. Dick (2008), Ho and Ishii (2011), Honka, Hortaçsu, and Vitorino (2017), Egan, Lewellen and Sunderam (2017), and Xiao (2018) estimate differentiated demand models for bank deposits. Egan, Hortaçsu, and Matvos (2017) distinguish between insured and uninsured deposits, and endogenize bank defaults and bank runs. Aguirregabiria, Clark, and Wang (2016) estimate a model of banks' geographic location of branches, and study the role of geographic risk diversification in the configuration of bank branch networks. In a recent paper, Wang, Whited, Wu, and Xiao (2018) imbed simple demand models for both deposits and loans into a corporate finance model in order to understand the impact of various financial frictions for the transmission of monetary policy. Given their focus, their models of deposits and loans are only at the national level, only for a subset of lenders, and do not allow for synergies between the two sides of the market. Similarly, Drechsler, Savov, and Schnabl (2017) study the role of market power for the transmission of monetary policy using a Dixit-Stiglitz model of monopolistic competition. Our paper extends all of these previous studies by considering an equilibrium model for both deposits and loans that allows for interconnections between these markets at the local level and for the effect of a bank's total liquidity on the costs of loans in local markets. This rich connectivity is necessary to answer the specific questions we pose here, but also a contribution in its own right.

We are also related to a recent set of papers that take advantage of the exogenous variation provided by the shale boom to study the extent to which banks use their branch networks to transfer funds from one local market to another (Gilje, 2017; Gilje, Loutskina, and Strahan, 2016; Loutskina and Strahan, 2015; Petkov, 2017; and Cortés and Strahan, 2017). Our paper complements in different ways the empirical findings by Gilje, Loutskina, and Strahan (2016). First, our empirical analysis of the relationship between the geographic location of a bank's branches (deposits) and loans extends to all the local markets (counties) in US. Second, we study the contribution of local market power to the geographic flow of banks' funds. Third, our approach for the identification of the effect of total deposits on local loans exploits more general sources of exogenous variation than those associated to local catastrophic events or discoveries of natural resources. Finally, our structural model allows us to identify the different sources of transaction costs for the flow of funding, and to perform counterfactual experiments to evaluate the effect on credit of reducing these costs.

The rest of the paper proceeds as follows. In the next section we describe the data and present descriptive evidence on the geographic dispersion of deposits and loans. In Section 3 we describe our model and in Section 4 we explain how we go about estimating it. Section 5 presents our empirical results and Section 6 describes our counterfactual experiments. Finally, Section 7 concludes.

2 Data and descriptive evidence

2.1 Data sources

We combine two data sources at the bank-county level. Branch and deposit information is collected from the Summary of Deposit (SOD) data provided by the Federal Deposit Insurance Corporation (FDIC). Information on mortgage loans comes from the Home Mortgage Disclosure Act (HMDA) data set.

The SOD dataset is updated June 30th of each year and covers all depository institutions insured by the FDIC, including commercial banks and saving associations. The dataset includes information at the branch level on deposits, location, and bank affiliation. Based on the county identifier of each branch, we can construct a measure of the number of branches and total deposits for each bank in each county.[5]

Under HMDA, most mortgage lending institutions are required to disclose information on the mortgage loans that they originate, refinance, or purchase in a given year.[6] At the level of financial institution, county, and year, we have information on the number and volume of mortgage applications, mortgage loans actually issued, and mortgage loans subsequently securitized.[7] The type of institutions reporting to HMDA include both depository institutions and non-depository institutions, mainly Independent Mortgage Companies (IMCs).[8] By definition, only the former, including banks and thrifts, can be matched with the SOD data.[9] In addition to this matching issue, this paper focuses on depository institutions because these are the institutions that rely heavily on branching and deposits to fund their loans. By contrast, IMCs rely on wholesale funding and mortgage brokers (Rosen, 2011). Focusing on depository institutions is consistent with the research questions addressed in this paper. Nevertheless, to take into account competition in the mortgage market from non-depository institutions, we aggregate at the county-year level the total number and volume of loan mortgages from these institutions, and we use this information in our construction of market shares and in the estimation of our structural model of demand and supply of mortgages.

County level data on socioeconomic characteristics are obtained from various products of the US Census Bureau. Population counts by age, gender, and ethnic group are obtained from

[5] A small proportion of branches in the SOD dataset (around 5% of all branches) have zero recorded deposits. These might be offices in charge of loans or administrative issues. We exclude them in our analysis.

[6] There are some geographic restrictions on loan reporting. According to the Community Reinvestment Act (CRA), large banks have to report information on all their loans regardless of the geographic location. Furthermore, regardless their size, lenders located in an MSA must report on loans originated in an MSA, though they can choose not to report loans outside MSAs. Only small lenders located outside of MSAs do not have to report. This means that the HMDA dataset may not include mortgage loans issued by small banks and originated in rural locations. However, according to the US census, about 83 percent of the population lived in an MSA region during our sample period. Therefore, HMDA captures most residential mortgage lending activity.

[7] We do not make use of the information on securitization as, for our purposes, what lenders do with their loans after making them is not of primary interest. Rather we are interested in knowing whether and to what extent loans were made. Summary stats on securitization are reported below.

[8] IMCs are for-profit lenders that are neither affiliated nor subsidiaries of banks' holding companies.

[9] We match banks in the SOD and HMDA datasets using their certificate number (provided by FDIC to every insured depository institution) or/and their RSSD number (assigned by Federal Reserve to every financial institution). We match thrifts using their docket numbers. We match financial institutions supervised by the OCC through the Call Reports, which allow us to match information from SOD and HMDA.

the Population Estimates. Median household income at the county level is extracted from the State and County Data Files, whereas income per capita is provided by the Bureau of Economic Analysis (BEA). Information on local business activities such as two-digit-industry level employment and number of establishments is provided by the County Business Patterns. Finally, detailed geographic information, including the area and population weighted centroid of each county, and locations of the landmarks in the US, is obtained from the Topologically Integrated Geographic Encoding and Referencing system (TIGER) dataset.

We also use information on county-level house prices for 2742 counties between 1990-2015 from the Federal Housing Finance Agency (see Bogin, Doerner and Larson, 2019), and county-level bankruptcy data from the U.S. Bankruptcy Courts.[10] House-price and bankruptcy data allow us to control for county differences in prices and risk that have an impact on the evolution over time of demands for deposits and loans.

We derive bank-level characteristics from balance sheets and income statement information in the banks' quarterly reports provided to the different regulatory bodies: the Federal Reserve Board (FRB)'s Report on Condition and Income (Call Reports) for commercial banks, and the Office of Thrift Supervision's (OTS) Thrift Financial Report (TFR) for saving associations.

Four features of our data and empirical approach deserve specific discussion. First, we have data on mortgage loans at the bank-county-year level, but not on other forms of bank credit. Ideally, we would incorporate information on other types of bank loans, but, to our knowledge, such data are not publicly available at the bank-county-year level.[11] However, mortgage loans represent the most substantial part of bank loans, and even of bank assets. Using bank level information from the 2010 Call Reports, Mankart, Michaelides, and Pagratis (2018) show that mortgages account for between 62% and 72% of all bank loans, and between 38% and 45% of total bank assets, where the range of values captures heterogeneity in these ratios according to bank size (i.e., larger banks tend to have a smaller share of mortgage loans in total loans and assets). They also report that bank deposits represent between 68% and 85% of total bank liabilities. These patterns hold in our sample too. Looking at mortgage loans in assets for lenders in the HMDA dataset, the median share is just below 40% at the start of our sample, rising to over 50% at the time of the financial crisis. Therefore,

[10] More specifically, we use Table F 5A Business and Nonbusiness Bankruptcy County Cases Commenced, by Chapter of the Bankruptcy Code During the 12-Month Period Ending June 30, 2007.

[11] Some data on small-business loans are available, but, for most of our sample period, only very large banks (ie. those with more than $1 billion in assets) were required to reveal lending activity.

our focus on deposits and mortgages, though motivated by data availability, captures a very substantial fraction of total bank liabilities and assets, respectively.

Second, it should also be pointed out that our empirical focus will be on *stocks* of deposits and *flows* of new loans. The assumption underlying this decision is that consumers can choose in every period where to put their entire stock of deposits and where to get new loans (or where to refinance their loan), as opposed to either the stock of both deposits and loans or only new deposits and new loans.[12] We are justified in making this assumption by the fact that switching costs are much higher for loans than they are for deposits. While there are some time costs involved in moving deposits, they are typically less important than the financial penalties imposed when moving mortgage loans from one financial institution to another.

Third, neither of the main data sets contains information on interest rates. Access to deposit and loan interest rate data would be crucial if our objective were to separately estimate demand and marginal cost. However, that is not the main purpose of this paper. To answer all the main empirical questions we consider, we need to estimate the value of consumers' willingness-to-pay net of banks' marginal costs for the different deposit and loan products, as well as how net willingness-to-pay depends on different variables such as local bank branches. We show that these primitives can be identified without information on prices of deposits and loans, and require imposing weaker conditions than if we were trying to separately identify demand and marginal costs.

Finally, it is worth pointing out that we define our markets to be counties, the primary administrative divisions for most states. Markets determine the set of branches that are competing with each other for consumer deposits and loans within a geographic area. Although other market definitions, such as State or Metropolitan Statistical Area, have been employed in some previous empirical studies on the US banking industry, many have considered county as their measure of geographic market (see for instance Huang, 2008; Gowrisankaran and Krainer, 2011; and Uetake and Wanatabe, 2018).

[12] We include refinances in our sample since borrowers can move their mortgage to a new bank when they refinance, and so the refinance decision looks very similar to the initial decision to get a mortgage with a lender.

2.2 Summary statistics

We concentrate on the period 1998-2010. Our matched sample includes $7,821$ depository banks and $3,655$ non-depository banks in $3,146$ counties.[13] The dataset contains a total of $2,582,308$ bank-county-year observations for depository banks, and $4,465,718$ bank-county-year observations for non-depository banks.

Table 1 presents summary statistics from our working sample. The top panel provides bank-level statistics based on $61,486$ bank-year observations for depository banks, and the bottom panel includes county-level statistics using $40,844$ county-year observations. The median number of counties where a bank obtains deposits from its branches is only 2, while the median number of counties where a bank sells mortgage loans is 8. The branch network of a bank is geographically more concentrated than its network of counties where it provides loans. Similarly, in the panel of county-level statistics, the median number of banks providing deposit services in a county is only 4, but the median number of banks selling mortgages is 34. The median Herfindahl-Hirschman indexes (HHI) are $2,535$ for deposit markets and 633 for loan markets. A possible explanation for these figures is that branches are more important to attract consumer demand for deposits than to attract demand for loans, but branches are costly to create and operate (e.g., fixed costs). Our estimation of the structural model in section 5 provides evidence supporting this explanation.[14]

Figures 1a and 1b show the evolution of the number of banks and branches per county for our SOD-HMDA matched sample and for all the banks in SOD, respectively. In our matched sample, at the start of our sample period there were just over 5 banks and about 20 branches per county. These numbers increased steadily to over 7 and almost 28, respectively. The increase coincides with the rolling out of Riegle-Neal, which permitted banks to branch across state lines. Over the same time period the percentage of multi-state banks increased from less than 1% to around 7%. Though figures 1a and 1b provide very similar pictures for the evolution of the number of banks and branches over this period, there are some differences. Notably, in the full sample the number of banks and branches increases steadily until just

[13] Of these counties, 3119 have deposits in at least one year during the sample period: there are 27 counties with zero deposits at every year during the sample period. However, we observe positive amounts of mortgage loans from depository banks (and from non-depository banks) in these counties with zero deposits. These 27 counties with no deposits but positive mortgages are rural or suburban markets where people live and make investments but where there are no bank branches. We keep all $3,146$ counties in our analysis.

[14] Between 50% and 60% of the banks, throughout the sample period, have positive deposits in more than two counties. This is important for the estimation of our structural model, and more specifically for the identification of the effect of a bank's total deposits on its local loans.

after the crisis and then decreases slightly. In the estimation of our model, we account for competition in deposit and loan markets from banks and other financial institutions which are not matched in our working sample. The deposits and mortgage loans of all the unmatched financial institutions are aggregated at the county level.

Table 1
Summary Statistics

Bank Level Statistics: Depository Banks (61,486 bank-year obs.)

Variable	Mean	S. D.	Pctile 5	Median	Pctile 95
Number of branches	15.7	116.8	1.0	4.0	35.0
Number of counties with deposits > 0	4.1	18.2	1.0	2.0	10.0
Number of counties with new loans > 0	29.9	149.6	1.0	8.0	69.0
Total deposits (in million $)	1,018	11,700	38	153	1,797
Total new loans (in million $)	188	3,181	0.8	13	259
Interest rate of deposits (%)	1.50	1.89	0.61	1.45	2.43
Interest rate of loans (%)	3.52	0.67	2.56	3.49	4.59
Securitized loans (first year) (%)	20.78	31.10	0.00	0.00	88.63

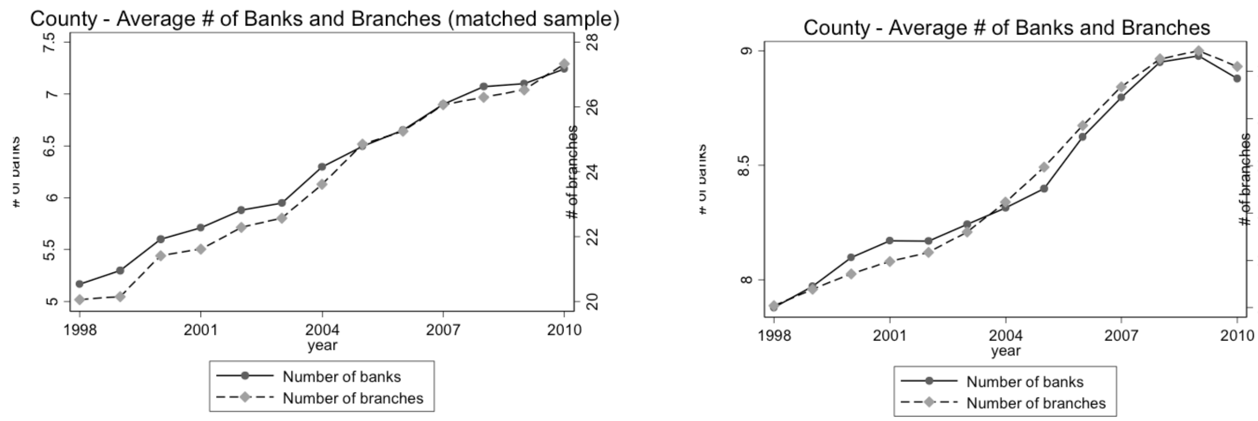
County Level Statistics (40,844 county-year obs.)

Variable	Mean	S. D.	Pctile 5	Median	Pctile 95
Depository banks					
Number of branches (per county)	23.7	63.8	0.0	6.0	104.0
Number of banks with deposits > 0	6.3	8.6	0.0	4.0	21.0
Number of banks with loans > 0	45.0	40.0	6.0	34.0	125.0
HHI market of deposits	3179	2087	1103	2535	8016
HHI market of new loans	881	858	257	633	2273
Deposits per capita (in ,000 $)	14.2	12.0	5.2	12.4	27.5
New loans per capita (in ,000 $)	3.4	4.2	0.4	2.1	10.6
Securitized loans (first year) (%)	51.24	19.26	17.46	52.73	81.02
Non-depository banks					
Number of banks with loans > 0	109	85	15	89	227
New loans per capita (in ,000 $)	1.6	2.3	0.1	0.9	5.8
Securitized loans (first year) (%)	75.80	12.77	53.04	78.36	90.84
Demographics					
Income per capita (in ,000 $)	27.9	8.1	18.1	26.6	41.7
Population (in ,000 people)	93.4	301.2	3.0	25.2	396.4
Share population $\leq$ 19 (in %)	27.4	3.4	22.2	27.3	33.2
Share population $\geq$ 50 (in %)	33.3	6.3	23.4	33.0	44.2
Annual change in house price index	3.0	5.7	-5.9	3.0	12.3
Number of bankruptcy filings per year	435	1506	6	107	1799

Figure 1: Number of banks and branches by county

(a) SOD-HMDA Matched Sample

(b) All SOD Banks



2.3 Descriptive evidence of the geographic imbalance of deposits and loans

In this subsection we present evidence on the extent to which deposits and loans are geographically imbalanced. We adapt the measures of residential segregation used in sociology and in labour economics, to capture the dissimilarity between the geographic distributions of deposits and loans, either for a single bank or for all the banks.

Figure 2 presents maps with the geographic distribution of counties' positions as net borrowers or net lenders. We present these maps for three different years: 1999, 2004, and 2009. For every county-year, we calculate the county's share of deposits over aggregate national deposits. Similarly, we calculate the county's share of new loans over the aggregate amount of new loans in the nation. Based on these shares, we construct at the county level the index S_{L-D} that represents the difference between the county's share of new mortgage loans and its share of deposits. The values of the indexes S_{L-D} provides the geographic distribution of the borrowing and lending positions of the different counties. By construction, the mean of these indexes over the counties is equal to zero, and there are positive and negative values for net borrowing and net lending counties, respectively.

We sort counties into four groups: (i) counties belonging to top 10 percentiles of S_{L-D} (Share Loans >> Share Deposits); (ii) counties between the 10th and 50th percentiles of S_{L-D} (Share Loans > Share Deposits); (iii) counties between the 50th and 90th percentiles of S_{L-D} (Share Loans < Share Deposits); and (iv) counties belonging to the bottom 10 percentiles of S_{L-D} (Share Loans << Share Deposits).

Figure 2 shows clear evidence of deposit and loan imbalances, with some regions having very high share of deposits, but low share of loans and vice versa. It also reveals regional patterns in the net borrowing/lending position of counties, the most obvious of which is that counties in the interior of the US tend to be net lenders while markets in the two coasts are typically net borrowers.

There are also interesting changes over time related to the mortgage boom and the subsequent financial crisis at the end of the decade. For instance, in 1999 a number of counties in California were in the bottom 10 percentiles of S_{L-D}, indicating that their share of total deposits was much larger than their share of total loans. By 2004 almost all counties in the state were in the top 10 percentiles, likely reflecting the build up of mortgage debt during the housing boom. Five years later, during the crisis, many counties had flipped again with deposit share higher than loan shares.

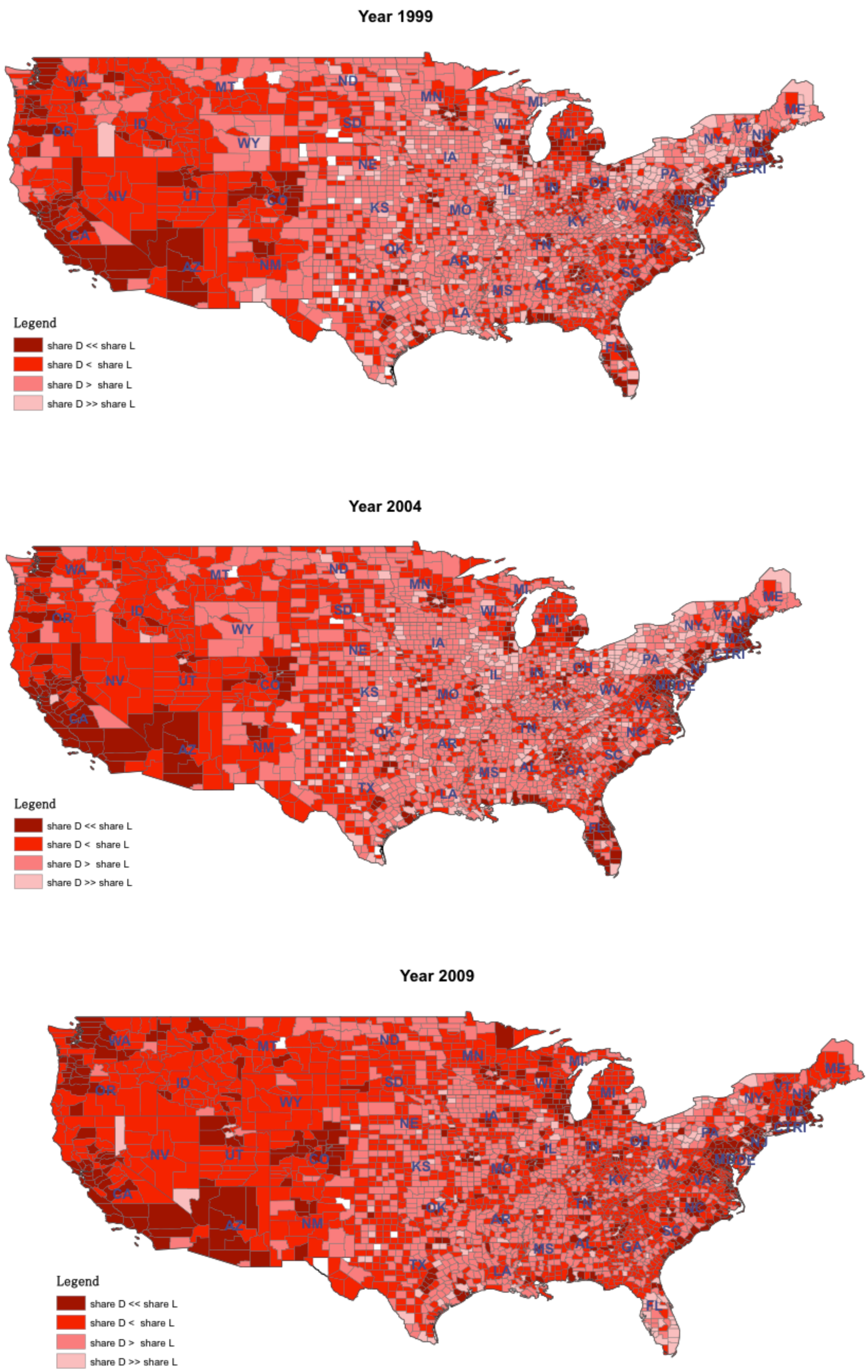
Borrowing from the literature on racial geographic segregation, we consider the following index to capture the *imbalance* of deposits and loans at the bank level.

$$II_{jt} = \frac{1}{2} \sum_{m=1}^{M} \left| \frac{q^d_{jmt}}{Q^d_{jt}} - \frac{q^\ell_{jmt}}{Q^\ell_{jt}} \right|, \tag{1}$$

where q^d_{mt} and q^ℓ_{mt} represent the amount of deposits and loans, respectively, in county m and year t for bank j, and Q^d_{jt} and Q^ℓ_{jt} represent the bank's total amounts of deposits and loans. This index is a measure of the imbalance of a bank's deposits and loans or, alternatively, a measure of the bank's home bias. For instance, an imbalance score equal to zero represents an extreme case of home bias, i.e., the bank's geographic distributions of loans and deposits are identical. At the other extreme, an imbalance index equal one means that the bank gets all its deposits in markets where it does not provide loans, and sells loans only in markets where does not have deposits, an extreme case of geographic diffusion of loans.[15]

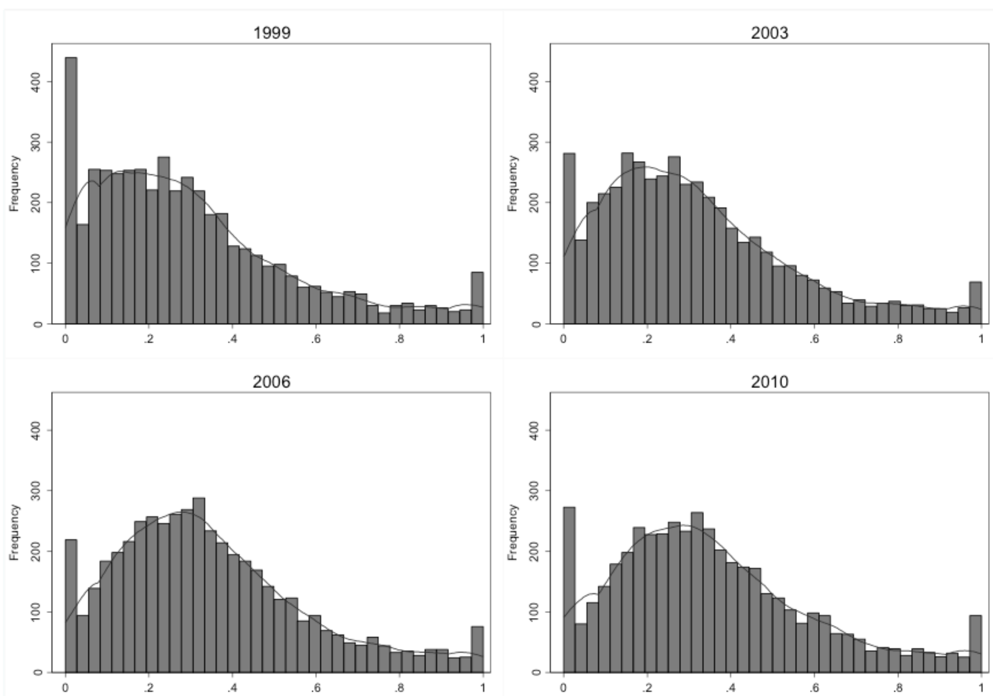
[15] In the appendix we present evidence for the segregation of deposits and loans using *State* as the measure of *market*. That is, we redefine a market m to be the state where the deposits are collected or the loans are made and calculate the imbalance index of each bank. Naturally there are many more banks that only operate in one market and so we focus on those banks that operate in multiple markets (slightly less than half of banks in any given year). We can see that the distribution shifts considerably to the left.

Figure 2: Distribution of borrower/lender counties



From Figure 3 we can see that, while most banks are involved to some degree in the transfer of funds across geographic locations, there are some with a strong home bias. In each year there is a mass of banks with a score equal to zero. Some of these are of course banks with presence in only a single county and so the fraction of banks in this group falls over time as banks expand their branch networks. At the other extreme we find some banks with very high scores. In fact, the index is greater than 0.5 for more than a third of the banks. We can also see a noticeable shift to the right of the distribution over time, suggesting that more deposit funds are being distributed outside the county where they were generated (home county). Table A1 in the appendix looks at the evolution over time for the top ten banks (ranked by assets).[16] For these banks the imbalance scores are 0.45 in 1999, 0.43 in 2004 and 0.52 in 2009.

Figure 3: Imbalance Indexes between Deposit and Loan Distributions–Bank level



This increase over time is also noticeable in Figure 4 which presents the time series of a national level imbalance index calculated using county level observations. This imbalance index is defined as:

$$II_t = \frac{1}{2}\sum_{m=1}^{M}\left|\frac{Q^d_{mt}}{Q^d_t} - \frac{Q^\ell_{mt}}{Q^\ell_t}\right|, \tag{2}$$

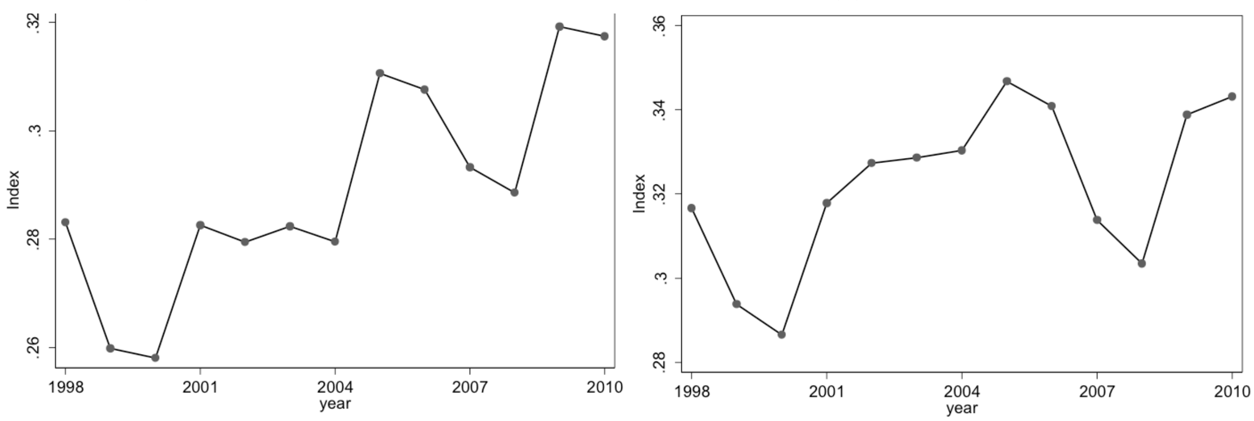
[16] Specifically, since we are interested in calculating the imbalance index for each of these banks in 1999, 2004 and 2009, we calculate the average assets for banks in these three years and then rank banks accordingly.

where $\frac{Q^d_{mt}}{Q^d_t}$ and $\frac{Q^\ell_{mt}}{Q^\ell_t}$ are the shares of county m in the aggregate national amounts of deposits and new mortgage loans, respectively. This index measures the imbalance of funds between geographic locations. Figure 4a presents the national index for our matched sample. It exhibits a cyclical trend, although the overall level of variation is not large, i.e., between 0.26 and 0, 32. Figure 4b uses the full sample that includes also non-depository banks. It displays the same general trend.

Figure 4: Time Series of the National Imbalance Index

(a) SOD-HMDA Matched Sample

(b) All SOD Banks



3 Model

Consider an economy with M geographic markets, indexed by $m \in \mathcal{M} = \{1, 2, ..., M\}$, and J banks, indexed by $j \in \{1, 2, ..., J\}$. Let $\mathcal{M}^d_j$ represent the set of markets where bank j has branches and sells deposits. Similarly, $\mathcal{M}^\ell_j$ represents the set of markets where bank j sells loans. This set of markets $\mathcal{M}^\ell_j$ includes all the markets where the bank has branches, but it may include other markets where the bank has contacts with mortgage brokers that provide clients for the bank. Therefore, $\mathcal{M}^\ell_j$ includes the set $\mathcal{M}^d_j$ but it can be larger, i.e., $\mathcal{M}^d_j \subseteq \mathcal{M}^\ell_j$. We take networks $\{\mathcal{M}^d_j\}^J_{j=1}$ and $\{\mathcal{M}^\ell_j\}^J_{j=1}$ as given and focus on the endogenous determination of the amounts of deposits and loans in the equilibrium of this static model of multi-market oligopoly competition.[17]

[17]One can think of these networks as being the result of a dynamic game of market entry-exit decisions with networks. More specifically, this dynamic game has the structure of an Ericson-Pakes model (Ericson and Pakes, 1995). Every year, banks decide their respective deposit and loan networks for the following year (i.e., one year time-to-build). Banks take as given their pre-determined networks and compete, statically, in prices for deposits and loans.

Each local market is populated by *savers* who demand deposit products, and *investors* who demand loan products. Importantly, some savers will also be investors and vice versa. Banks sell deposit and loan products in these local markets. These products are horizontally differentiated between banks due to different product characteristics and to spatial differentiation within a local market. This view of banks' services as differentiated products is in the spirit of previous papers in the literature such as Degryse (1996), Schargrodsky and Sturzenegger (2000), Cohen and Mazzeo (2007 and 2010), Gowrisankaran and Krainer (2011), or Egan, Hortacsu, and Matvos (2017), among others. A novel feature of our model, that is key for the purposes of our analysis, is that it introduces endogenous links between deposit and loan markets and between these markets at different geographic locations. The structure of the model has similarities with demand systems in two-sided markets (see Rysman (2004) and Fan (2013)).

Bank j sells deposit products in every market in the set $\mathcal{M}_j^d$, and sells loan products in every market in the set $\mathcal{M}_j^\ell$.[18] The (variable) profit function of bank j is equal to interest earnings from new loans (pre-existing loans are considered as pre-determined fixed profits), minus payments to depositors, minus costs of managing deposits and loans,[19] and minus the costs (or returns) from the bank's activity in interbank wholesale markets:

$$\Pi_j = \sum_{m=1}^{M} p_{jm}^\ell \; q_{jm}^\ell + p_{jm}^d \; q_{jm}^d - C_{jm}\left(q_{jm}^\ell, q_{jm}^d\right) - \left(r_0 + c_{j0}\right) B_j, \tag{3}$$

where p_{jm}^ℓ and p_{jm}^d are prices for loans and deposits, respectively, for bank j in market m, and q_{jm}^ℓ and q_{jm}^d are the corresponding amounts of loans and deposits. Note that, typically, the price for loans will be positive ($p_{jm}^\ell > 0$) because borrowers pay a positive interest rate to obtain a loan, while the price of deposits is typically negative ($p_{jm}^d < 0$) because the bank pays savers to attract their deposits. Market $m = 0$ represents the interbank wholesale market; r_0 is the interbank interest rate; B_j is the net borrowing position of bank j at the interbank market; and c_{j0} is a bank-specific transaction cost associated with using the interbank market. The interbank interest rate is determined by the Federal Reserve, and is exogenous in this model.

The function $C_{jm}\left(q_{jm}^\ell, q_{jm}^d\right)$ represents the cost of managing deposits and loans in market m. This cost includes the expected cost of loan default or pre-payment, as well as the expected cost reduction associated with loan securitization. A bank's resources constraint

[18] For the sake of notational simplicity, we omit in this section the time subindex t.

[19] The cost of managing loans includes the expected cost of loan default and loan prepayment.

implies that, $B_j = Q_j^\ell - Q_j^d$, where $Q_j^\ell \equiv \sum_{m=1}^M q_{jm}^\ell$ and $Q_j^d \equiv \sum_{m=1}^M q_{jm}^d$ are bank j's total new loans and deposits, respectively.[20] Solving this restriction in the profit function, we have that $\Pi_j = \sum_{m=1}^M p_{jm}^\ell \; q_{jm}^\ell + p_{jm}^d \; q_{jm}^d - \widetilde{C}_{jm}\left(q_{jm}^\ell, q_{jm}^d\right)$, with $\widetilde{C}_{jm}\left(q_{jm}^\ell, q_{jm}^d\right) \equiv C_{jm}\left(q_{jm}^\ell, q_{jm}^d\right) + (r_0 + c_{j0})\ (q_{jm}^\ell - q_{jm}^d)$. For the rest of the paper we do not include the term $(r_0 + c_{j0})$ $(q_{jm}^\ell - q_{jm}^d)$ explicitly in the variable cost function, but it should be understood that marginal costs include the component $r_0 + c_{j0}$ with positive sign for loans and negative for deposits.

Given the interest rate in the interbank market, r_0, the equilibrium of our model determines the amounts of loans and deposits of every bank in every local market, and it also determines the net position of a bank in the interbank market, since $B_j = Q_j^\ell - Q_j^d$. Then, given the net positions of the private banks, the position of the Federal Reserve, represented by B_0, is also endogenously determined, such that the interbank market clears; that is, the equilibrium condition $\sum_{j=1}^J B_j + B_0 = 0$ is satisfied.

Section 3.1 describes the demand system for deposits and loans. Section 3.2 presents our specification of bank variable costs. The equilibrium of the model is described in section 3.3.

3.1 Demand for deposit and loan products

(a) Demand for deposit products. There is a population of H_m^d savers in market m. Each saver has a fixed amount of wealth that we normalize to one unit.[21] A saver has to decide whether to deposit her unit of savings in a bank, and if so, in which one. Due to transportation costs, savers consider only banks with branches in their own local market. In other words, banks can get deposits only in markets where they have branches.[22] Banks provide differentiated deposit products. The (indirect) utility for a saver from depositing her wealth in bank j in market m is (omitting the individual-saver subindex in variables u_{jm}^d and ε_{jm}^d):

$$u_{jm}^d = \mathbf{x}_{jm}^d \; \beta^d - \alpha^d \; p_{jm}^d + \xi_{jm}^d + \varepsilon_{jm}^d. \tag{4}$$

$\mathbf{x}_{jm}^d$ is a vector of characteristics of bank j (other than the deposit interest rate) and market m that are valued by depositors and observable to the researcher, such as the number of branches of bank j in the market, n_{jm}. The vector β^d contains the marginal utilities of the characteristics $\mathbf{x}_{jm}^d$. Variable p_{jm}^d is the price of deposit services (i.e., consumer fees minus

[20] More precisely, we have that $B_j = S_j^\ell + Q_j^\ell - Q_j^d$, where S_j^ℓ is the stock of live pre-existing loans. However, S_j^ℓ is pre-determined and it does not have any effect on variable profits.

[21] See section 4 for a description of our measure of this 'unit' and of the number of consumers in the market, as well as our approach to deal with possible misspecification of these values.

[22] Honka, Hortaçsu, and Vitorino (2017) provide evidence of the importance of local branch presence for the decision to open bank accounts.

the deposit interest rate), and α^d is the marginal utility of income. The term ξ^d_{jm} represents other characteristics of bank j in market m that are observable and valuable to savers but unobservable for us as researchers. Variables ε^d_{jm} represent savers' idiosyncratic preferences, and we assume that they are independently and identically distributed across banks with type 1 extreme value distribution. The utility from the outside alternative is normalized to zero. Let $s^d_{jm} \equiv q^d_{jm}/H^d_m$ be the market share of bank j in the market for deposits at location m. The model implies that:

$$s^d_{jm} = \frac{1\left\{m \in \mathcal{M}^d_j\right\} \ \exp\left\{\mathbf{x}^d_{jm}\ \beta^d - \alpha^d\ p^d_{jm} + \xi^d_{jm}\right\}}{1 + \sum_{k=1}^{J} 1\left\{m \in \mathcal{M}^d_k\right\} \ \exp\left\{\mathbf{x}^d_{km}\ \beta^d - \alpha^d\ p^d_{km} + \xi^d_{km}\right\}}, \tag{5}$$

where $1\{.\}$ is an indicator function such that $1\left\{m \in \mathcal{M}^d_j\right\}$ is a dummy variable that indicates whether bank j has branches in market m.

The vector of product characteristics $\mathbf{x}^d_{jm}$ includes three elements that are important for the implications of the model: (i) the number of branches (n_{jm}); (ii) the bank's share of the local market for loans (s^ℓ_{jm}); and (iii) the bank's total amount of deposits (Q^d_j). The number of branches captures the effects of consumer transportation costs as well as consumer awareness about the bank's presence. By including the bank's market share of loans, s^l_{jm}, in the demand for deposits (and, as we will show below, the share of deposits in the demand for loans), we try to capture, in a simple and parsimonious way, not only economies of scope and other synergies in the demand for deposits and loans (i.e. one-stop banking), but also the two-sided-market nature of the banking business (see Section 4 of Vives, 2016).[23] The bank's total deposits capture consumers' concerns for the probability of default or bank-run. Therefore, we have that,

$$\mathbf{x}^d_{jm}\beta^d = \mathbf{z}_m\ \beta^d_0 + \beta^d_n h(n_{jm}) + \beta^d_\ell\ s^\ell_{jm} + \beta^d_Q\ \ln Q^d_j. \tag{6}$$

$\mathbf{z}_m$ is a vector of exogenous market characteristics that can affect the value of the outside alternative, and $h(.)$ is a monotonic function. We can also generalize this specification to incorporate the consumer valuation of a bank's number of branches in neighboring counties. We use the function $s^d_{jm} = d_{jm}(p^d_{jm}, s^\ell_{jm}, Q^d_j)$ to represent the demand for deposits,

[23] To capture economies of scope or synergies we could consider a demand model for deposits and loans that endogenizes consumers' decisions to bundle or not their deposits and mortgage products in the same bank, as in Allen, Clark, and Houde (2018). However, our dataset does not contain any information on consumer bundling decisions, even at the aggregate level. Our specification involves a relatively simple approach to capture this complementarity in demand. Furthermore, by including market shares, our specification tries to capture other type of positive spillover effects between the demand of loans and deposits that operate not only at the level of an individual consumer but at the market level, e.g., two-sided markets.

where, for notational convenience, we include explicitly as arguments the endogenous variables $(p^d_{jm}, s^\ell_{jm}, Q^d_j)$.

(b) Demand for loan products. Each local market is also populated by investors / borrowers. Let H^ℓ_m be the number of new borrowers in market m. Each (new) borrower is endowed with an investment project that requires 1 unit of loans.[24] The set of possible choices that a borrower has is not limited to the banks that have branches in the market. There are banks that sell mortgages in the market but do not have physical branches (recall that $\mathcal{M}^d_j \subseteq \mathcal{M}^\ell_j$). However, borrowers may also value the geographic proximity of the bank as represented by the branches of the bank in the local market. Banks provide differentiated loan products. For a borrower located in market m, the (indirect) utility of a loan from bank j is:

$$u^\ell_{jm} = \mathbf{x}^\ell_{jm}\ \beta^\ell - \alpha^\ell\ p^\ell_{jm} + \xi^\ell_{jm} + \varepsilon^\ell_{jm}. \tag{7}$$

The variables and parameters in this utility function have a similar interpretation as in the utility for deposits presented above. Variable p^ℓ_{jm} represents the interest rate of a loan from bank j in market m. We also assume that the variables ε^ℓ_{jm} are identically distributed across banks with type 1 extreme value distribution, and that the utility from the outside alternative is normalized to zero. Let $s^\ell_{jm} \equiv q^\ell_{jm}/H^\ell_m$ be the market share of bank j in the market for loans at location m. According to the model, we have that:

$$s^\ell_{jm} = \frac{1\left\{m \in \mathcal{M}^\ell_j\right\}\ \exp\left\{\mathbf{x}^\ell_{jm}\ \beta^\ell - \alpha^\ell\ p^\ell_{jm} + \xi^\ell_{jm}\right\}}{1 + \sum_{k=1}^{J} 1\left\{m \in \mathcal{M}^\ell_k\right\}\ \exp\left\{\mathbf{x}^\ell_{km}\ \beta^\ell - \alpha^\ell\ p^\ell_{km} + \xi^\ell_{km}\right\}}. \tag{8}$$

As was the case for deposits, the vector of product characteristics $\mathbf{x}^\ell_{jm}$ includes: (i) the number of branches (n_{jm}); (ii) the bank's share of the local market for deposits (s^d_{jm}); and (iii) the bank's total amount of deposits in all the markets (Q^d_j). As explained above for the demand for deposits, the number of branches captures consumer transportation cost and consumer awareness, and the amount of local deposits portrays economies of scope between deposits and loans for the consumer if using the same bank. Consumers value a bank's total amount of deposits because it is related to the bank's risk of liquidity shortage and failure.[25] Thus, we have that

$$\mathbf{x}^\ell_{jm}\beta^\ell_m = \mathbf{z}_m\ \beta^\ell_0 + \beta^\ell_n h(n_{jm}) + \beta^\ell_d\ s^d_{jm} + \beta^\ell_Q\ \ln Q^d_j, \tag{9}$$

[24] In our empirical application, this will be a real estate investment.

[25] Borrowers are concerned with bank failure because there is a risk that the new acquiring bank may not renew their loans.

We use the function $s^{\ell}_{jm} = \ell_{jm}(p^{\ell}_{jm}, s^{d}_{jm}, Q^{d}_{j})$ to represent the demand for loans.

Naturally, there will be many instances where bank j's share of loans in market m is zero, and one might be concerned that the observed zeroes were mostly the result of a "small sample" problem arising because of a small number of potential customers in a county (see Ghandi, Lu, and Shi (2018) for a discussion). However, this is not the reason for zeroes in our case. Most of the bank-county-year observations in our dataset where loans are zero occur because they are actually zero in the population. That is, there are many counties where a bank does not make any loans.[26]

(c) Demand system for deposits and loans. The demand system can be represented by the equations $s^{\ell}_{jm} = \ell_{jm}(p^{\ell}_{jm}, s^{d}_{jm}, Q^{d}_{j})$ and $s^{d}_{jm} = d_{jm}(p^{d}_{jm}, s^{\ell}_{jm}, Q^{d}_{j})$. For the moment, let us consider this demand system for a single bank, taking as given prices of loans and deposits for the rest of the banks. This system establishes links between the amount of deposits and loans in the same local market and across different geographic markets. Taking prices as given, the solution of this system of equations with respect to market shares $\{s^{\ell}_{jm}, s^{d}_{jm}\}$ implies the *reduced form demand system*:

$$s^{d}_{jm} = f^{d}_{jm}\left(\mathbf{p}^{d}_{j}, \mathbf{p}^{\ell}_{j}\right) \quad \text{and} \quad s^{\ell}_{jm} = f^{\ell}_{jm}\left(\mathbf{p}^{d}_{j}, \mathbf{p}^{\ell}_{j}\right), \tag{10}$$

where $\mathbf{p}^{d}_{j}$ and $\mathbf{p}^{\ell}_{j}$ are the vectors with bank j's interests rates for deposits and loans, respectively, in every local market where this bank is active. Loans (deposits) in a local market depend on the bank's interest rates for loans and deposits in every market where the bank operates. Therefore, the demand-price derivatives, $\partial f^{d}_{jm}/\partial p^{\ell}_{jm}$ or $\partial f^{\ell}_{jm}/\partial p^{d}_{jm}$, incorporate *local-* and *global-multiplier effects.* In the Appendix, we derive the expressions for these derivatives as functions of the derivatives in the original structural demand functions.

3.2 Variable cost function

We consider the following specification for the variable cost function:

$$\tilde{C}_{jm}\left(q^{\ell}_{jm}, q^{d}_{jm}\right) = \left[\mathbf{x}^{d}_{jm}\ \gamma^{d} + \omega^{d}_{jm}\right]\ q^{d}_{jm} + \left[\mathbf{x}^{\ell}_{jm}\ \gamma^{\ell} + \omega^{\ell}_{jm}\right]\ q^{\ell}_{jm}. \tag{11}$$

[26] Suppose to the contrary that the observed zeroes were mostly the result of a small number of potential customers in a county. Under this condition, when a bank has a positive amount of loans in a county the number of loan customers that the bank serves should be quite small. This hypothesis is clearly rejected in our data. For the bank-county-year observations with a positive amount of loans at year t and zero loans at year t-1 (5183 observations, 0.37% of the sample), the sample mean for the number of loans is 112 and the median is 22. Similarly, for the observations with a positive amount of loans at year t and zero loans at year t+1 (3263 observations, 0.23% of the sample), the sample mean for the number of loans is 48 and the median is 10. For most of these observations the number of served customers is not small, which contradicts the hypothesis that the zeroes are mostly the result of a small sample of potential customers.

Therefore, the marginal costs for deposits and loans are $c^d_{jm} \equiv \mathbf{x}^d_{jm}\ \gamma^d + \omega^d_{jm}$ and $c^\ell_{jm} \equiv \mathbf{x}^\ell_{jm}\ \gamma^\ell + \omega^\ell_{jm}$, respectively. Variables ω^ℓ_{jm} and ω^d_{jm} are unobservable to the researcher. The vector of observable variables $\mathbf{x}_{jm}$ includes the same variables as in the demand equations:

$$\begin{aligned} \mathbf{x}^d_{jm}\ \gamma^d &= \mathbf{z}_m\ \gamma^d_0 + \gamma^d_n\ h(n_{jm}) + \gamma^d_\ell\ s^\ell_{jm} + \gamma^d_Q\ \ln Q^d_j, \\ \mathbf{x}^\ell_{jm}\ \gamma^\ell &= \mathbf{z}_m\ \gamma^\ell_0 + \gamma^\ell_n\ h(n_{jm}) + \gamma^\ell_d\ s^d_{jm} + \gamma^\ell_Q\ \ln Q^d_j. \end{aligned} \tag{12}$$

The terms $\gamma^d_n\ h(n_{jm})$ and $\gamma^\ell_n\ h(n_{jm})$ portray economies of scale and scope between branches of a bank in the same market. Some costs of providing deposits and loans are shared by multiple branches. The terms $\gamma^d_\ell\ s^\ell_{jm}$ and $\gamma^\ell_d\ s^d_{jm}$ capture economies of scope in the management of deposits at the branch level. The component $\gamma^\ell_Q\ \ln Q^d_j$ captures how the marginal cost of loans declines with the bank's total volume of deposits Q^d_j.

3.3 Bank competition and equilibrium

A bank can charge a different interest rate for deposits (loans) at each local market. We assume that banks compete a la Nash-Bertrand. Therefore, each bank chooses its vectors of interest rates for deposits and loans, $\mathbf{p}_j \equiv \{p^d_{jm} : m \in \mathcal{M}^d_j;\ p^\ell_{jm} : m \in \mathcal{M}^\ell_j\}$, to maximize its profit.

A marginal change in the interest rate of deposits of bank j in county m has the following effects on the bank's profit: (i) the standard marginal revenue and marginal cost effect from deposits in the same county; (ii) the indirect effect on the profits from loans in the same county; (iii) the indirect effect on the profits from deposits in other counties where the bank operates; and similarly, (iv) the indirect effect on the profits from loans in other counties. That is,

$$\begin{aligned} &\underbrace{\left[q^d_{jm} + \left(p^d_{jm} - \frac{\partial \tilde{C}_{jm}}{\partial q^d_{jm}} \right) \frac{\partial f^d_{jm}}{\partial p^d_{jm}} \right]}_{\textit{direct effect: local deposits}} \quad + \quad \underbrace{\left(p^\ell_{jm} - \frac{\partial \tilde{C}_{jm}}{\partial q^\ell_{jm}} \right) \frac{\partial f^\ell_{jm}}{\partial p^d_{jm}}}_{\textit{indirect effect: local loans}} \\ &\underbrace{+ \sum_{m' \neq m} \left(p^d_{jm'} - \frac{\partial \tilde{C}_{jm'}}{\partial q^d_{jm'}} \right) \frac{\partial f^d_{jm'}}{\partial p^d_{jm}}}_{\textit{indirect effect: deposits other counties}} \quad + \quad \underbrace{\sum_{m' \neq m} \left(p^\ell_{jm'} - \frac{\partial \tilde{C}_{jm'}}{\partial q^\ell_{jm'}} \right) \frac{\partial f^\ell_{jm'}}{\partial p^d_{jm}}}_{\textit{indirect effect: loans other counties}} \quad = \quad 0. \end{aligned} \tag{13}$$

We have a similar expression for the marginal condition of optimality with respect to the interest rate for loans. This set of marginal conditions of optimality for every bank j and every geographic market m determines an equilibrium of the model.

Using the logit structure, we now develop expressions that characterize the Bertrand equilibrium and that we use for the estimation of the model parameters and for our counterfactual experiments. In the Appendix, we show that the system of marginal conditions of optimality implies the following pricing equations:

$$\begin{aligned} p^d_{jm} - c^d_{jm} &= \frac{1}{\alpha^d(1-s^d_{jm})} - \frac{\beta^\ell_d}{\alpha^\ell} s^\ell_{jm} - \frac{\beta^d_Q + \beta^\ell_Q}{\alpha^\ell} \; (Q^\ell_j / Q^d_j) \\ p^\ell_{jm} - c^\ell_{jm} &= \frac{1}{\alpha^\ell(1-s^\ell_{jm})} - \frac{\beta^d_\ell}{\alpha^d} s^d_{jm} \end{aligned} \tag{14}$$

We can see that the spillover effects in the demands for loans and deposits generate an incentive to reduce price-cost margins in the two markets. The effect of the demand spillover on the price-cost margin, $-\dfrac{\beta^d_\ell}{\alpha_d} \; s^d_m$ and $-\dfrac{\beta^\ell_d}{\alpha_\ell} \; s^\ell_m$, has exactly the same magnitude as the direct spillover effect on a consumer's willingness to pay for the product. Similarly, the spillover effect from the bank's total deposits generates an incentive to reduce the price-cost margin in the deposit market.

For our empirical analysis, it is convenient to write the equilibrium conditions in terms of the market shares as the only endogenous variables. Let s^d_{0m} and s^ℓ_{0m} be the market shares of the outside alternative for deposits and loans in market m. The logit model implies that $\ln(s^d_{jm}/s^d_{0m}) = \mathbf{x}^d_{jm} \; \beta^d_m + \alpha^d \; p^d_{jm} + \xi^d_{jm}$. Subbing the pricing equations into this expression, we obtain the following system of equilibrium equations in terms of market shares:

$$\begin{aligned} y\left(s^d_{jm}, s^d_{0m}\right) &= \mathbf{x}^d_{jm} \; \beta^d - \alpha^d \; c^d_{jm} + \frac{\alpha^d \beta^\ell_d}{\alpha^\ell} s^\ell_{jm} + \left(\beta^d_Q + \beta^\ell_Q\right) \; (Q^\ell_j/Q^d_j) + \xi^d_{jm} \\ y\left(s^\ell_{jm}, s^\ell_{0m}\right) &= \mathbf{x}^\ell_{jm} \; \beta^\ell - \alpha^\ell \; c^\ell_{jm} + \frac{\alpha^\ell \beta^d_\ell}{\alpha^d} s^d_{jm} + \xi^\ell_{jm} \end{aligned} \tag{15}$$

where, for any value of the shares (s_j, s_0), the function $y\,(s_j, s_0)$ is defined as $\ln\left(\dfrac{s_j}{s_0}\right) + \dfrac{1}{1-s_j}$. Given the structure of the marginal costs as $c^\ell_{jm} = \mathbf{x}^\ell_{jm} \; \gamma^\ell + \omega^\ell_{jm}$ and $c^d_{jm} = \mathbf{x}^d_{jm} \; \gamma^d + \omega^d_{jm}$, we can represent the system of equilibrium equations as:

$$\begin{aligned} y\left(s^d_{jm}, s^d_{0m}\right) &= \mathbf{x}^d_{jm} \; \theta^d + \eta^d_{jm} \\ y\left(s^\ell_{jm}, s^\ell_{0m}\right) &= \mathbf{x}^\ell_{jm} \; \theta^\ell + \left(\beta^d_Q + \beta^\ell_Q\right) (Q^\ell_j/Q^d_j) + \eta^\ell_{jm} \end{aligned} \tag{16}$$

where the θ's are structural parameters that depend on both demand and marginal cost parameters. More specifically, we have that $\mathbf{x}^\ell_{jm} \; \theta^\ell \equiv \mathbf{z}_m \; \theta^\ell_0 + \theta^\ell_n \; h(n_{jm}) + \theta^\ell_d \; s^d_{jm} + \theta^\ell_Q \; \ln Q^d_j$, with $\theta^\ell_0 \equiv \beta^\ell_0 - \alpha^\ell \; \gamma^\ell_0$, $\theta^\ell_n \equiv \beta^\ell_n - \alpha^\ell \; \gamma^\ell_n$, $\theta^\ell_Q \equiv \beta^\ell_Q - \alpha^\ell \; \gamma^\ell_Q$, and $\theta^\ell_d \equiv \beta^\ell_d - \alpha^\ell \; \gamma^\ell_d + \alpha^\ell \beta^d_\ell / \alpha^d$.

The index $\mathbf{x}_{jm}^{d}\ \theta^{d}$ in the loans equation has the same structure. Similarly, the "error terms" in the deposit and loan equations depend on both demand and cost shocks: $\eta_{jm}^{d} \equiv \xi_{jm}^{d} - \alpha^{d}\ \omega_{mt}^{d}$ and $\eta_{jm}^{\ell} \equiv \xi_{jm}^{\ell} - \alpha^{\ell}\ \omega_{mt}^{\ell}$.

The vector of parameters θ, together with the exogenous variables of the model, contain all the information that we need to construct the equilibrium mapping of the model and obtain an equilibrium. Given this model structure, we do not need to separately identify demand and cost parameters. All our empirical results are based on the estimation of these parameters and the implementation of counterfactual experiments using the equilibrium mapping.

4 Estimation and identification of the structural model

The system of equations of the econometric model are:

$$\begin{aligned} y_{jmt}^{d} &= \mathbf{z}_{mt}'\ \theta_{0}^{d} + \sum_{n=1}^{n_{\max}} \theta_{n}^{d}(n)\ 1_{jmt}(n_{jmt} \geq n) + \theta_{\ell}^{d}\ s_{jmt}^{\ell} + \theta_{Q}^{d}\ \ln Q_{jt}^{d} + \eta_{jmt}^{d}, \\ y_{jmt}^{\ell} &= \mathbf{z}_{mt}'\ \theta_{0}^{\ell} + \sum_{n=1}^{n_{\max}} \theta_{n}^{\ell}(n)\ 1_{jmt}(n_{jmt} \geq n) + \theta_{\ell}^{\ell}\ s_{jmt}^{d} + \theta_{Q}^{\ell}\ \ln Q_{jt}^{d} + \eta_{jmt}^{\ell}, \end{aligned} \tag{17}$$

where $y_{jmt}^{d} \equiv y\left(s_{jmt}^{d}, s_{0mt}^{d}\right)$, $y_{jmt}^{\ell} \equiv y\left(s_{jmt}^{\ell}, s_{0mt}^{\ell}\right)$, $1_{jmt}(n_{jmt} \geq n)$ is the binary variable that indicates that the number of branches n_{jmt} is greater than or equal to n, and $\mathbf{z}_{mt}$ is a vector of market characteristics that captures the relative value of the outside alternative. More specifically, $\mathbf{z}_{mt}$ includes a housing price index and its growth, bankruptcy cases, income per capita, population, and age distribution.

(i) Market size and market shares for deposits and loans. To construct market shares we need first to construct market size variables H_{mt}^{d} and H_{mt}^{ℓ}. We use the following approach. First, we postulate that H_{mt}^{d} and H_{mt}^{ℓ} are proportional to the total population in county m at period t:[27] $H_{mt}^{d} = \lambda^{d}\ POP_{mt}$ and $H_{mt}^{\ell} = \lambda^{\ell}\ POP_{mt}$ where λ^{d} and λ^{ℓ} are positive constants and POP_{mt} is total population in county m at period t. Coefficients λ^{d} and λ^{ℓ} are chosen such that the the constructed market shares satisfy the model constraint that the sum of the market shares $\sum_{j} s_{jmt}^{d} = Q_{mt}^{d}/H_{mt}^{d}$ and $\sum_{j} s_{jmt}^{\ell} = Q_{mt}^{\ell}/H_{mt}^{\ell}$ are smaller than one for every county-year observation. More specifically, the values of these coefficients are $\lambda^{d} = \max_{m,t}\left\{\frac{Q_{mt}^{d}}{POP_{mt}}\right\}$ and $\lambda^{\ell} = \max_{m,t}\left\{\frac{Q_{mt}^{\ell}}{POP_{mt}}\right\}$, which in our data are are $\lambda^{d} = 548$ and $\lambda^{\ell} = 84$ measured in thousands of USD.

[27] We have also tried total county income, instead of county population. Our empirical results are robust to this.

Admittedly, using POP_{mt} as a measure of market size, and assuming that λ^d and λ^ℓ are constant across counties and over time, seems like a strong restriction. To control for measurement error, we include socioeconomic characteristics at the county-level as explanatory variables in the model. Among these characteristics is the number of applications for mortgage loans from the HMDA data set. One might wonder why we do not instead use the number of applications as our measure of market size in the mortgage markets. This is because, as explained in Agrawal et al (2018), many prospective borrowers apply multiple times for a loan before ultimately obtaining financing or abandoning their search altogether. According to their data on mortgages from a large government sponsored entity in the US, the overall median number of applications per person is nine, and the median for those who are ultimately financed is two. Therefore, although we know the number of applications, since the HMDA data do not allow us to identify individual applicants, we cannot be sure of the number of applicants. For this reason we do not use applications as our measure of market size, but instead use it to control for measurement error in our population measure.

(ii) Endogeneity. In the structural equations in (17), regressors s^ℓ_{jmt}, s^d_{jmt}, and $\ln Q^d_{jt}$ are endogenous variables of the model, and therefore correlated with the error terms η^d_{jmt} and η^ℓ_{jmt} because of simultaneity. Furthermore, though the number of branches n_{jmt} is not an endogenous variable in our structural model, we expect this variable to depend also on the supply and demand shocks in deposits and loan markets. Therefore, the number of branches is also an endogenous variable in the econometric model. We describe below our assumptions to deal with endogeneity.

Our strategy to identify the effect of a bank's total deposits on its local loans is in the same spirit as the approaches in Gilje, Loutskina, and Strahan (2016), Cortés and Strahan (2017), and Nguyen (2019). Gilje, Loutskina, and Strahan (2016) use shale gas discoveries in a county as exogenous shocks and study how they generate an increase in loans in other counties connected through branch networks. Similarly, Cortés and Strahan (2017) exploit exogenous variation provided by natural disasters, and Nguyen (2019) uses bank mergers. Our approach uses similar sources of exogenous variation, but is more general since it is not limited to dramatic local shocks. We show that after controlling for a rich fixed-effects specification of the unobservables that includes fixed effects at the bank-county, year, and county-year levels, it is possible to instrument a bank's total deposits using time-varying socioeconomic characteristics in other counties where the bank operates. We can apply this identification approach to every bank-county-year observation as long as the bank's network includes multiple counties and the county has more than one active bank, without relying on dramatic local shocks.

The identification and estimation of the model are based on four assumptions: (i) a rich fixed effects specification of the unobservables; the assumption that the remaining bank-county-year transitory shocks are (ii) not correlated with the observable exogenous county characteristics, and (iii) not serially correlated; and (iv) the bank-year effects are not correlated with observable exogenous county characteristics. Assumptions ID-1 to ID-4 provide a formal description of our identifying restrictions.

Assumption ID-1 [Fixed Effects]: The unobservables η^{d}_{jmt} and η^{ℓ}_{jmt} have the following component structure:

$$\eta^{d}_{jmt} = \eta^{d(1)}_{jm} + \eta^{d(2)}_{t} + \eta^{d(3)}_{mt} + \eta^{d(4)}_{jt} + \eta^{d(5)}_{jmt}. \tag{18}$$

$\eta^{d(1)}_{jm}$ represents bank-county fixed effects; $\eta^{d(2)}_{t}$ represents national level unobserved shocks; $\eta^{d(3)}_{mt}$ is county-year idiosyncratic shock; $\eta^{d(4)}_{jt}$ represents a bank-year idiosyncratic shock; and $\eta^{d(5)}_{jmt}$ is a bank-county-year specific shock. The error term in the loan equation has the same structure. ■

Assumption ID-2: The observable county characteristics in vector $\mathbf{z}_{mt}$ are strictly exogenous regressors with respect to the bank-county-specific shocks $\eta^{d(5)}_{jmt}$ and $\eta^{\ell(5)}_{jmt}$, i.e., for any pair of markets (m, m') and any pair of years (t, t'), we have that $\mathbb{E}\left(\mathbf{z}_{mt}\ \eta^{d(5)}_{jm't'}\right) = 0$ and $\mathbb{E}\left(\mathbf{z}_{mt}\ \eta^{\ell(5)}_{jm't'}\right) = 0$. ■

Assumption ID-3: Bank-county-year shocks $\eta^{d(5)}_{jmt}$ and $\eta^{\ell(5)}_{jmt}$ are not serially correlated. ■

Assumption ID-4: The observable county characteristics in vector $\mathbf{z}_{mt}$ are strictly exogenous regressors with respect to the bank-year idiosyncratic shocks $\eta^{d(4)}_{jt}$ and $\eta^{\ell(4)}_{jt}$, i.e., for any market m and bank j pair, we have that $\mathbb{E}\left(\mathbf{z}_{mt}\ \eta^{d(4)}_{jt}\right) = 0$. ■

Consider the following difference-in-difference (DiD) transformation of the structural equations of the model. First, a difference between the equations of two banks operating in the same county. This transformation eliminates the national-level shock, $\eta^{d(2)}_{t}$, and the county-year idiosyncratic shock, $\eta^{d(3)}_{mt}$, from the error term. Second, a time difference between the equations at two consecutive periods. This transformation eliminates the bank-county fixed effect, $\eta^{d(1)}_{jm}$, from the error term. That is,

$$\begin{aligned} \Delta\widetilde{y}^{d}_{jmt} &= \Delta\widetilde{\mathbf{x}}^{d}_{jm}\ \theta^{d} + \Delta\widetilde{\eta}^{d(4)}_{jt} + \Delta\widetilde{\eta}^{d(5)}_{jmt}, \\ \Delta\widetilde{y}^{\ell}_{jmt} &= \Delta\widetilde{\mathbf{x}}^{\ell}_{jm}\ \theta^{\ell} + \Delta\widetilde{\eta}^{\ell(4)}_{jt} + \Delta\widetilde{\eta}^{\ell(5)}_{jmt}. \end{aligned} \tag{19}$$

The $\sim$ symbol represents the difference between two banks operating in the same county, e.g., $\widetilde{y}_{jmt}^{d} \equiv y_{jmt}^{d} - y_{j_m^* mt}^{d}$, where j_m^* is a baseline bank active at county m that we select to make this transformation. The symbol Δ represents the time difference transformation, e.g., $\Delta\widetilde{y}_{jmt}^{d} \equiv [y_{jmt}^{d} - y_{j_m^* mt}^{d}] - [y_{jm,t-1}^{d} - y_{j_m^* m,t-1}^{d}]$.

We can also apply a third difference to eliminate the bank-year component of the error term. Let the $*$ symbol represent the difference between two counties where the bank is active, e.g., $y_{jmt}^{*d} \equiv y_{jmt}^{d} - y_{jm_j^* t}^{d}$, where m_j^* is a baseline county in the network of bank j. Therefore, we have the difference-in-difference-in-difference (DiDiD) transformation of the structural equations:

$$
\begin{aligned}
\Delta\widetilde{y}_{jmt}^{*d} &= \Delta\widetilde{\mathbf{x}}_{jm}^{*d}\ \theta^{d} + \Delta\widetilde{\eta}_{jmt}^{*d(5)}, \\
\Delta\widetilde{y}_{jmt}^{*\ell} &= \Delta\widetilde{\mathbf{x}}_{jm}^{*\ell}\ \theta^{\ell} + \Delta\widetilde{\eta}_{jmt}^{*\ell(5)}.
\end{aligned} \tag{20}
$$

Note this DiDiD transformation removes the bank's total deposits, $\ln Q_{jt}$, from the vector of explanatory variables. Therefore, this equation cannot be used to identify parameters θ_Q^d and θ_Q^ℓ. However, as we show below, these parameters can be identified from the DiD equation.

Assumptions ID-2, ID-3, and ID-4 imply moment conditions (or valid instrumental variables) in the transformed equations. First, assumptions ID-2 and ID-3 imply the following moment conditions in the DiDiD equations:

$$
\begin{aligned}
\mathbb{E}\left(\begin{bmatrix} \mathbf{z}_{mt} \\ \mathbf{x}_{km,t-s} \end{bmatrix} \Delta\widetilde{\eta}_{jmt}^{*d(5)}\right) &= 0, \\
\mathbb{E}\left(\begin{bmatrix} \mathbf{z}_{mt} \\ \mathbf{x}_{km,t-s} \end{bmatrix} \Delta\widetilde{\eta}_{jmt}^{*\ell(5)}\right) &= 0.
\end{aligned} \tag{21}
$$

for any $s \geq 2$. These moment conditions identify the parameters $\theta_n^d(n)$, $\theta_n^\ell(n)$, θ_ℓ^d, and θ_d^ℓ. These moment conditions combine dynamic panel models or Arellano-Bond moment conditions (Arellano and Bond, 1991) with BLP moment conditions (Berry, Levinsohn, and Pakes, 1995). The implicit instruments for the endogenous variables $\{n_{jmt}, s_{jmt}^d, s_{jmt}^\ell\}$ are lagged values (two lags or more) of the bank's number of branches, deposits, and loans, and also the lagged values of these variables for the other banks competing in the county.

Second, assumptions ID-2 and ID-4 imply the following moment conditions in the DiD equations. For any (m, m', j):

$$
\begin{aligned}
\mathbb{E}\left(\mathbf{z}_{m't}\ \left[\Delta\widetilde{\eta}_{jt}^{d(4)} + \Delta\widetilde{\eta}_{jmt}^{d(5)}\right]\right) &= 0, \\
\mathbb{E}\left(\mathbf{z}_{m't}\ \left[\Delta\widetilde{\eta}_{jt}^{\ell(4)} + \Delta\widetilde{\eta}_{jmt}^{\ell(5)}\right]\right) &= 0.
\end{aligned} \tag{22}
$$

These moment conditions identify the parameters θ_Q^d and θ_Q^ℓ. Intuitively, these moment conditions imply that we can use the exogenous socioeconomic characteristics in markets other than m where the bank is active in the deposit market, i.e., $\{\mathbf{z}_{mt}$ for $m' \neq m$ with $m' \in \mathcal{M}_{jt}^d\}$, to instrument the total amount of deposits $\ln Q_{jt}^d$. The characteristics in other markets do not have a direct effect in the structural equation for market m, i.e., they satisfy an exclusion restriction. By assumption ID-2 and ID-4, they are not correlated with the error term $\Delta\widetilde{\eta}_{jt}^{d(4)} + \Delta\widetilde{\eta}_{jmt}^{d(5)}$, therefore, they are valid instruments. Furthermore, the model implies that these characteristics should have an effect on the total volume of deposits of the bank, therefore, they are relevant instruments.

We jointly estimate all the parameters of the model using a GMM estimator in the spirit of those in the dynamic panel data literature. We apply a two-step optimal GMM estimator and obtain standard errors robust of heterocedasticity and serial correlation.

5 Estimation results

Tables 4 and 5 present estimation results of the structural equations for deposits and loans, respectively. We report both OLS Fixed-Effects (without instrumenting) and GMM (DiD and DiDiD) estimates. As shown in Table 1, banks provide loans in many more counties than they obtain deposits. As a result, the number of observations in the estimation of the loan equations is almost ten times the number of observations in the estimation of the deposit equation. Note also that the number of observations, both for deposits and loans, is larger in the GMM estimations than in the Fixed-Effects. This is because the variable for the housing price index has missing values for some county-year observations. While this variable is included in the OLS-FE estimations (together with other county socioeconomic characteristics), it is not included in the GMM estimation because it disappears in the within-county-year differencing (i.e., it is perfectly collinear with the county-year fixed effects).

By construction, the right-hand side of the equilibrium equations expressed in (17) represents consumer willingness-to-pay net of marginal cost. In fact, it is equal to the social value of the products at the bank-county-year level, relative to the value of the outside alternative. For convenience, we refer to these values as the *net willingness-to-pay* (or *net-wtp*). The parameters θ capture the causal effect of different variables on the *net-wtp.*

Unfortunately, the net-wtp and the θ parameters are not measured in monetary units (dollars) but in utils. Furthermore, the variance of extreme value unobservables can be different in the demands for loans and deposits, implying that the θ parameters in these two equations are not directly comparable.

Nevertheless, the dependent variables in the left-hand-side of the equilibrium equations are very close to logarithm of county-level market shares, $\ln(s^{d}_{jmt})$ and $\ln(s^{\ell}_{jmt})$. Therefore, we can draw comparisons between the θ parameters of the two equations by interpreting them as elasticities (if the explanatory variable is also in logarithms) or semi-elasticities.

(i) OLS-FE versus GMM-DiD estimates. The two sets of estimates provide similar qualitative results, but there are significant quantitative differences. Relative to GMM, the OLS method underestimates the effect of the number of branches and the magnitude of economies of scope. The main difference between the two sets of estimates is in the effect of total deposits on local loans and deposits. The estimated OLS elasticities with respect to total deposits are 0.39 for local deposits and 0.18 for loans, while the GMM estimates are 0.06 and 0.38, respectively. The Hansen-Sargan test of over-identifying restrictions and the test of no serial correlation have values close to one, supportinng the validity of our moment conditions / instruments. For the rest of the paper, we concentrate on the GMM estimates.

(ii) Number of branches. The number of branches in the county has a substantial effect on the net-wtp for a deposit product. The marginal effect of an additional branch declines with the number of branches: a second branch increases the net-wtp / log-share by 82%; a third branch by 50%; a fourth branch by 41%; a fifth branch 75%; and subsequent branches by (on average) 1%. The effect of the number of branches on the net-wtp / log-share of a loan product is also important, but smaller than for deposits: a second branch increases the net-wtp / log-share by 14%; a third branch by 13%; a fourth branch by 3%; a fifth branch by 10%; and subsequent branches by 1%.[28]

In the data and in our model, a bank needs at least one branch in the county to obtain deposits. That is not case for loans. Therefore, we can identify the effect of the first branch on the net-wtp for a loan product. The estimate is 136%, i.e., the first branch increases very substantially the demand for loan products.

[28] The estimated parameters for the effect of the fifth branch look strange because they break the monotonicity of the regression function with respect to the number of branches. However, there is nothing special about the fifth branch. This apparent non-monotonicity is an artifact of the specification, and in particular of considering a linear specification with respect to the number of branches, for branches greater than a value n_{max}. For any choice of n_{max}, we get a non-monotonicity at this value. This non-monotonicity becomes weaker when we increase the value of n_{max}. For instance, for $n_{max} = 10$ we cannot reject monotonicity. However, for values of n_{max} greater than 4, the choice of n_{max} only affects the estimates of the parameters associated with the variables "$1(n \geq n_{max})$" and "# branches above n_{max}", and the rest of the parameters are not affected at all. Note that there are very few observations where the number of branches is greater than 5.

(iii) Economies of scope between deposits and loans at the county level. We identify significant economies of scope between deposits and loans. Doubling the amount of deposits of a bank in a county implies a 30% increase in the net-wtp / market share of the bank's loans in the same market. The elasticity of deposits with respect to loans is 0.04 which is much smaller but still significant.

(iv) Effect of total deposits. A bank's amount of deposits at the national level has a substantial effect on the bank's net-wtp / log-share of product loans at every local market where it operates: a 100% increase in a bank's total deposits implies an 38% increase in the market share for loans at every county. This provides strong evidence that banks' internal liquidity facilitates lending.

(v) County characteristics. The OLS-FE estimation includes socioeconomic county characteristics as control variables. Income per-capita, the housing price index, and the number of bankruptcy filings all have substantial effects on the value of a loan product relative to the outside alternative. The effect of the housing price index, with an elasticity of 0.60, is particularly important. As expected, bankruptcy filings have a negative and significant effect, with an elasticity of -0.04.

Table 4
Estimation of Structural Equation for Deposits
Sample Period: 1998-2010[1]

Variable	OLS Fixed Effects	GMM DiD & DiDiD
Number of branches		
First branch ($1\{n_{jmt} \geq 1\}$)	–	–
Second branch ($1\{n_{jmt} \geq 2\}$)	0.5317*** (0.0116)	0.8242*** (0.0114)
Third branch ($1\{n_{jmt} \geq 3\}$)	0.2837*** (0.0092)	0.5052*** (0.0114)
Fourth branch ($1\{n_{jmt} \geq 4\}$)	0.2173*** (0.0094)	0.4170*** (0.0128)
Fifth branch ($1\{n_{jmt} \geq 5\}$)	0.2611*** (0.0114)	0.7526*** (0.0139)
# of branches in county above 5th	0.0326*** (0.0032)	0.0153*** (0.0007)
Econ. of scope and total depo		
log own loans in county	0.0211*** (0.0013)	0.0471*** (0.0017)
log own total deposits	0.3918*** (0.0124)	0.0658*** (0.0026)
Market characteristics		
log County Income	0.2649** (0.0429)	-
log County Population	-0.5335*** (0.0775)	-
Share Population age ≤ 19	3.4127*** (0.6374)	-
Share Population age ≥ 50	2.4334*** (0.4134)	-
log housing price index	0.2676*** (0.0254)	-
log number of bankruptcy filings	0.0067 (0.0046)	-
log number of loan applications	-0.0062 (0.0077)	-
Bank × County Fixed Effects	YES	YES (implicit in DiD)
Time Dummies	YES	YES (implicit in DiD)
County × Time Dummies	NO	YES (implicit in DiD)
Number of observations	204,152	255,371
R-square	0.2772	-
Hansen-Sargan test: p-value	-	0.5091
No serial correlation-m2: p-value	-	0.5971

Note 1: In parentheses, robust standard errors (clustered at bank-county) of serial correlation and heteroscedasticity. * means p-value < 0.05; ** means p-value < 0.01; *** means p-value< 0.001

Table 5
Estimation of Structural Equation for Loans
Sample Period: 1998-2010[1]

Variable	OLS Fixed Effects	GMM DiD & DiDiD
Number of branches		
First branch ($1\{n_{jmt} \geq 1\}$)	0.1373 (0.0930)	1.3693*** (0.0672)
Second branch ($1\{n_{jmt} \geq 2\}$)	0.1754*** (0.0172)	0.1436*** (0.0159)
Third branch ($1\{n_{jmt} \geq 3\}$)	0.0908*** (0.0183)	0.1369*** (0.0182)
Fourth branch ($1\{n_{jmt} \geq 4\}$)	0.0758** (0.0204)	0.0369 (0.0219)
Fifth branch ($1\{n_{jmt} \geq 5\}$)	0.0801** (0.0228)	0.0998*** (0.0217)
# of branches in county above 5th	0.0060* (0.0024)	0.0162*** (0.0007)
Econ. of scope and total depo		
log own deposits in county	0.1059*** (0.0075)	0.3010*** (0.0068)
log own total deposits	0.1833*** (0.0035)	0.3829*** (0.0011)
Market characteristics		
log County Income	-0.0194 (0.0411)	-
log County Population	-0.6769*** (0.0602)	-
Share Population age $\leq$ 19	-0.9071 (0.5175)	-
Share Population age $\geq$ 50	-0.2373 (0.3360)	-
log housing price index	0.6070*** (0.0257)	-
log number of bankruptcy filings	-0.0472*** (0.0064)	-
log number of loan applications	0.4525*** (0.0075)	-
Bank × County Fixed Effects	YES	YES (implicit in DiD)
Time Dummies	YES	YES (implicit in DiD)
County × Time Dummies	NO	YES (implicit in DiD)
Number of observations	1,503,938	1,836,655
R-square	0.2546	-
Hansen-Sargan test (p-value)	-	0.2997
No serial correlation-m2 (p-value)	-	0.9270

Note 1: In parentheses, robust standard errors (clustered at bank-county) of serial correlation and heteroscedasticity. * means p-value < 0.05; ** means p-value < 0.01; *** means p-value< 0.001

6 Counterfactual experiments

Using the estimated model, we implement counterfactual experiments to measure the effects economies of scope, branch networks, and local market power have on the geographic segregation of deposits and loans. We also study the impact of a deposit tax and national aggregate shocks. For all the experiments, we use the GMM estimates for the structural parameters θ, obtain the model residuals, and then apply OLS to estimate the five different components in the error terms η_{jmt}^{d} and η_{jmt}^{ℓ}.

We measure the effects of these counterfactuals by looking at three statistics or outcome variables: (a) the aggregate imbalance index, II, that we have defined in equation (2) and whose evolution we presented in Figure 4; and (b) the share of total national mortgage loans of the 2500 counties with the least amount of credit, and the share for the 100 counties with the most. In the data, the bottom 2500 counties and top 100 counties in terms of credit account for 22% and 40% of the US population, respectively. For the sake of presentation, we refer to the group of 2500 counties at the bottom in the distribution of loans (always before the experiments) as the *smaller/poorer* counties, and to the 100 counties at the top in the distribution of loans as the *larger/richer* counties.

The statistics that we present here try to capture a key trade-off in the geographic distribution of credit. A higher imbalance index implies that a larger share of bank funds is moved across counties such that credit can be used in those locations with more demand for loans. However, this movement of bank funds can generate not only winners but also losers. Some counties may end up with very limited amounts of credit.

Table 6 presents results from our counterfactual experiments. We now describe the motivation, implementation, and results of these experiments.

Experiment 1. First, we look at the importance of branch networks. We consider the counterfactual equilibrium that would arise if banks could only operate in one state. This experiment tries to evaluate the effect on the geographic segregation of deposits of a regulation that prohibits banks from operating branch networks in multiple states, as was the case prior to the Riegle-Neal Act of 1994. We divide every multi-state bank in our sample into different independent banks, one for each state. The main channel for the effect of this counterfactual is that the total volume of deposits of a bank is limited to the deposits from counties in the same state. The decline of $\theta_{Q}^{d} \ln Q_{jt}^{d}$ and $\theta_{Q}^{\ell} \ln Q_{jt}^{d}$ implies reductions in the net values of deposits and loans, respectively. Given that the estimate of parameter θ_{Q}^{ℓ} is substantially larger than θ_Q^d (i.e., 0.38 versus 0.06), the implied reduction in local loans is substantially larger than the reduction in local deposits. The specific effects on a county depend on the presence of multi-state banks before the experiment. We find that the imbalance index declines substantially, from 0.30 to 0.22. Smaller/poorer counties obtain more credit under the experiment, increasing from 10% to 12%. In contrast, the larger/richer counties experience a substantial reduction in the amount of credit they receive, falling from 56% to 50%. The main reason for this reduction of credit in richer counties is that multi-state banks have a stronger presence in these counties. Therefore, it seems that Riegle-Neal has improved substantially the geographic diffusion of loans, but has benefited especially larger/richer counties with a stronger demand for credit.

Experiment 2. In this experiment, we study the effects of eliminating scope economies or synergies between deposits and loans. We set the parameters θ_ℓ^d and θ_d^ℓ to zero and compute the new equilibrium of the model. We are more interested in the effect of local economies of scope in reducing the geographic diffusion of credit than on their effect of increasing the net value for loans and deposits. Therefore, we compensate for this effect by increasing the constant terms in the two structural equations such that the sample mean of the net value remains constant when evaluated at the observed sample values. Given that the estimate of parameter θ_d^ℓ is significantly larger than θ_ℓ^d (i.e., 0.30 versus 0.05) the effect of this experiment on the net value of local loans is stronger than the effect on local deposits. We find that the imbalance index increases from 0.30 to 0.33. This reallocation has a negative effect on smaller/poorer counties that now receive only a 8% share of total loans instead of the original 10%. However, it has a negligible effect on larger/richer counties that still receive 56% . Economies of scope have a significant effect on the geographic distribution of credit.

Experiment 3. This experiment evaluates the effect of eliminating county heterogeneity in local market power. We impose the restriction that every county has 4 banks in its deposit market and 34 banks in its loan markets. These values correspond to sample medians of these variables. We find very substantial effects associated with this counterfactual experiment. The imbalance index increases from 0.30 to 0.42, and the share of credit for smaller/poorer counties from 10% to 13%. Medium size counties also benefit (from 34% to 37% share of credit). The main losers from this reallocation are larger/richer counties with a decline in their share of credit from 56% to 50%. According to this experiment, limited competition in small and medium size counties play a very important role in the amount of credit that these counties receive.

Experiment 4. We evaluate how a counterfactual tax on deposits would affect the provision of credit and its geographic distribution. We implement this experiment by reducing by 20% the constant term in the equation for the net value of deposit products. Since we have estimates of net value structural parameters but not separate estimation of demand and marginal costs, we are not specific about the way the tax is implemented or the relative incidence of the tax on prices, consumer surplus, and bank profits. Instead, we consider that the tax reduces the net surplus of deposits by 20%. The imbalance index is reduced from 0.30 to 0.26, and the share of credit by larger/richer counties from 56% to 52%. The share of smaller/poorer increases by one percentage point. According to this experiment, a tax on deposits is not geographically neutral, but has effects on the geographic diffusion of credit.

Experiment 5. Finally, we investigate to what extent national aggregate shocks (e.g., business cycle, financial crisis, monetary policy) affect the geographic distribution of deposits and loans. We implement this experiment by setting to zero the national level aggregate shocks in the equations for deposits and loans: $\eta_t^d = \eta_t^\ell = 0$ at every year t. The effects are modest. The imbalance index declines from 0.30 to 0.29. Interestingly, smaller/poorer (larger/richer) receive less (more) credit when we remove aggregate shocks. It seems that aggregate shocks have not been geographically neutral during this period, and they have been slightly beneficial for smaller counties.

Table 6
Counterfactual Experiments

Outcome Variable	**Data**	**Exp. 1** No m.s.n.	**Exp. 2** No ec.s.	**Exp. 3** No h.m.p.	**Exp. 4** Tax depo	**Exp. 5** No agg.
Imbalance index	0.30	0.22	0.33	0.42	0.26	0.29
Bottom 2500 counties: share of credit	10%	12%	8%	13%	11%	9%
Top 100 counties: share of credit	56%	50%	56%	50%	52%	57%

Experiment 1: Remove multi-state branch networks ("No m.s.n.": No multi-state networks).
Experiment 2: Remove economies of scope ("No ec.s.": No economies of scope).
Experiment 3: Remove county heterogeneity in local market power ("No h.m.p.": No het. market power).
Experiment 4: 20% tax on deposits ("Tax dep.": Tax on deposits).
Experiment 5: Removes aggregate national shocks. ("No agg..": No aggregate shocks).

7 Conclusions

In this paper we use data from the Summary of Deposit and Home Mortgage Disclosure Act data sets for the period 1998-2010 to study the extent to which deposits and loans are segregated, and to investigate the factors that contribute to this imbalance. We make two main contributions.

First, we adapt techniques developed in sociology and labor to measure the degree of segregation of deposits and loans. Our *imbalance indexes* provide information on the transfer of funds within branch networks of US banks, and across counties. Our results reveal that the majority of banks exhibit a strong home bias and some regions have limited access to credit relative to their share of deposits.

Second, we develop and estimate a structural model of bank oligopoly competition that admits interconnections across locations and between deposit and loan markets. The equilibrium of the model allows for rich interconnections across geographic locations and between deposit and loan markets such that local shocks in demand for deposits or loans can affect endogenously the volume of loans and deposits in every local market. The estimated model shows that a bank's total deposits has a very significant effect on the bank's market shares in loan markets. We also find evidence that is consistent with significant economies of scope between deposits and loans at the local level.

An important advantage of our structural approach is that we can study counterfactual scenarios in which we adjust parameters or impose relevant policy-related restrictions. Our counterfactual experiments show that multi-state branch networks contribute significantly to the geographic flow of credit, but benefit especially larger/richer counties. Local market power, on the other hand, has a substantial negative effect on the geographic flow of credit. Limited competition in small and medium size counties play a very important role in restricting the amount of credit that these counties receive.

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8 Appendix–Additional Tables and Figures

Figure 5: Imbalance Indexes between Deposit and Loan Distributions–Bank level, with *market* measured at the State level

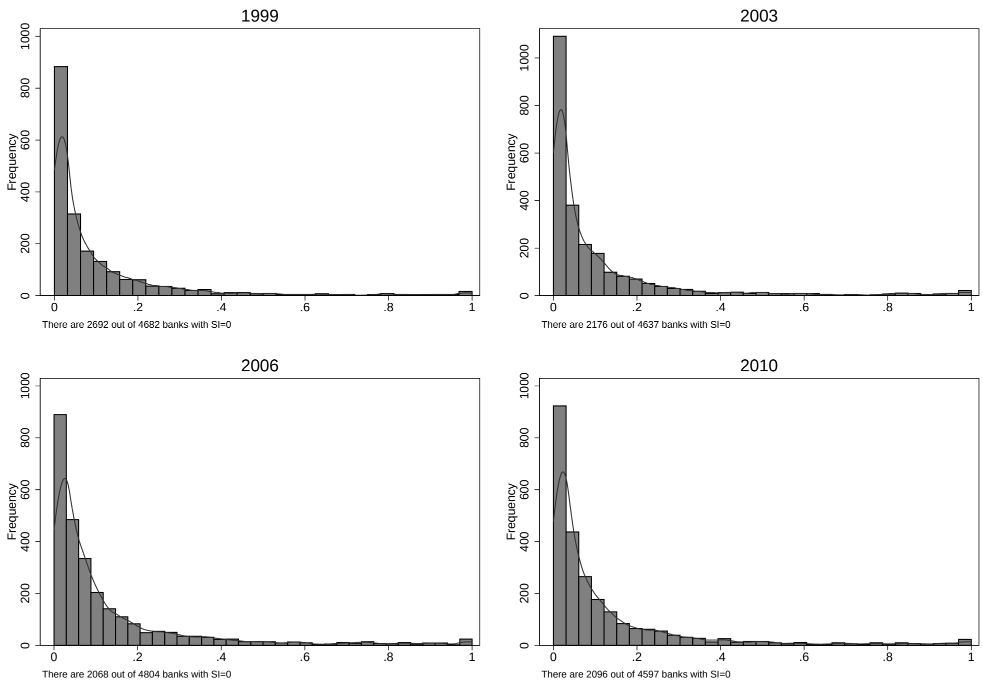


Table A1

Evolution of the Imbalance Index of the top 10 banks (by assets)

Rank by Avg. Asset	Bank Name	II_{1999}	II_{2004}	II_{2009}
1	BANK OF AMERICA NA	0.50	0.35	0.43
2	WACHOVIA BANK NATIONAL ASSN	0.38	0.41	0.55
3	WELLS FARGO BANK NA	0.33	0.51	0.51
2	CITIBANK NATIONAL ASSN	0.37	0.38	0.76
5	U S BANK NATIONAL ASSN	0.65	0.45	0.49
6	SUNTRUST BANK	0.89	0.43	0.61
7	PNC BANK NATIONAL ASSN	0.27	0.36	0.77
8	BRANCH BANKING&TRUST CO	0.27	0.34	0.33
9	KEYBANK NATIONAL ASSN	0.37	0.61	0.46
10	REGIONS BANK	0.43	0.44	0.29
Average		0.45	0.43	0.52

9 Appendix–For online publication only

9.1 Construction of the Matched Sample from HMDA and SOD

An institution in the Home Mortgage Disclosure Act (HMDA) dataset can be uniquely identified by the combination of two variables. The first is the "Agency code," which indicates the supervisory/regulatory agency of the HMDA reporting institution. There are six types of agency codes in HMDA dataset: (1) Office of the Comptroller of the Currency (OCC), (2) Federal Reserve System (FRS), (3) Federal Deposit Insurance Corporation (FDIC), (4) Office of Thrift Supervision (OTS), (5) National Credit Union Administration (NCUA), and (6) Department of Housing and Urban Development (HUD). Each agency type contains both depository and non-depository institutions., but only depository institutions can be matched with the Summary of Deposit (SOD) data.

The second variable used to identify an institution in HMDA is the "Respondent/reporter ID" (RID). For all non-depository institutions, RID is the institution's Federal Tax ID number. For depository institutions, the RID is either the charter or certificate number, depending on the agency code, which can then be matched with the corresponding bank identifiers in the SOD. The meaning of RID by agency types is summarized in Table A2:

Table A2

Code	Regulatory Agency	Meaning of RID
OCC	Office of the Comptroller of the Currency	Charter number
FRS	Federal Reserve System	RSSD number
FDIC	Federal Deposit Insurance Corporation	FDIC certificate number
OTS	Office of Thrift Supervision	RSSD number

It should be noted that all HUD institutions are non-depository, and so they cannot be matched with SOD and they are not included in the above Table. In addition, credit unions (NCUA) are not reported in the SOD, and so cannot be matched with HMDA at the bank-county level. Therefore, they are not included in the matched sample either.[29]

Using the combination of RID and agency code as shown in Table A2, HMDA institutions can be matched with SOD institutions at the bank-county-year level. Doing so generates our matched sample. Table A3 compares the matched and unmatched samples in 2004. Consistent with the criteria reported in Avery et. al. (2007), banks that are not obliged to report to HMDA are (1) small (as can be seen from the amount of assets,[30] the amount of deposits, the number of branches, and the number of counties in which they operate), or (2) are not in the residential-mortgage business (as can be seen from the smaller amount of mortgages reported in Table A3), or (3) have offices exclusively in rural (nonmetropolitan)

[29] The credit union CALL report data can be found on the NCUA?s website (https://www.ncua.gov/analysis/Pages/call-report-data.aspx). Therefore, it is possible to match credit unions between HMDA and SOD at the institutional level.

[30] Most banks in the matched SOD sample in 2004 have assets greater than $300 million, which is consistent with the asset criterion for reporting to HMDA in that year.

areas (as can be seen from the lower percentage of activity in MSAs in terms of deposits or branches for the unmatched sample). For these banks, we only know their county-level deposits, but not their county-level loans, although their bank-level mortgage loans are available from the CALL report data. For the purpose of our analysis, we have to drop these unmatched banks, which account for 15% of the total deposits and 10% of the total mortgage loans in year 2004.

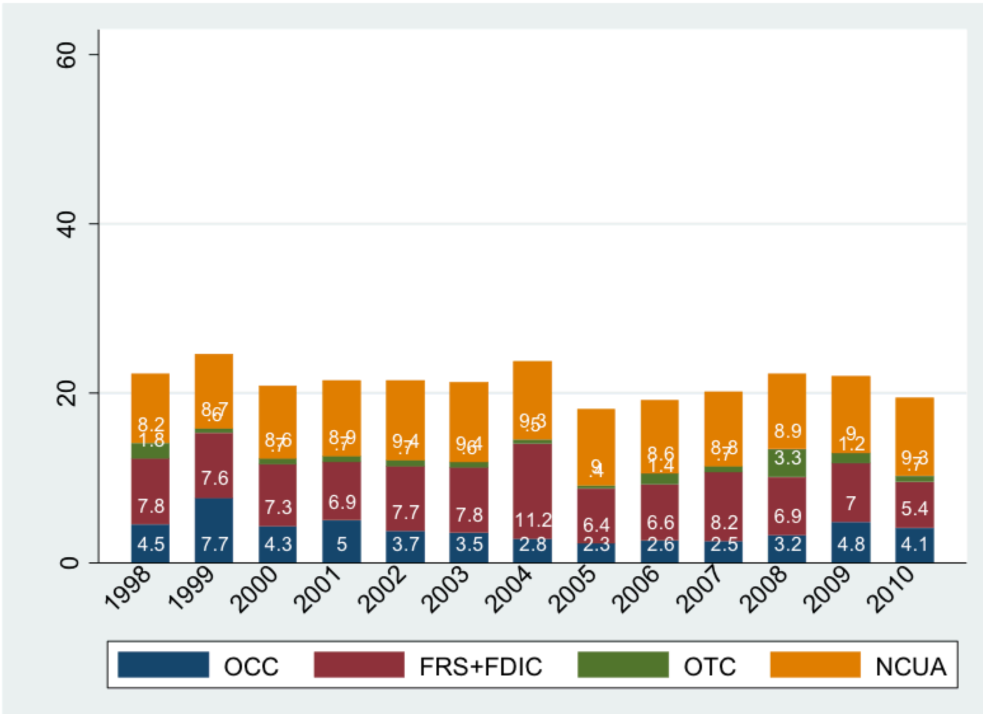
Figure 6a reports the share of deposits of the unmatched banks in the SOD datasets. First, credit unions cannot be matched at the bank-county level, therefore they are counted as the unmatched banks. They account for about 10% of total deposits. Second, some depository banks in SOD are exempt from reporting to HMDA, and so they belong to the unmatched sample. Figure 6b reports the share of mortgage provision of the unmatched institutions in the HMDA datasets. Other than credit unions, these are mainly the non-depository institutions. We explicitly model both the decision of the matched banks and these non-depository banks. Before 2006, the non-depository banks contributed about 50% of total credits. Since 2007, their contribution dropped to less than 40%, which reflects the changes since the financial crisis.

Table A3

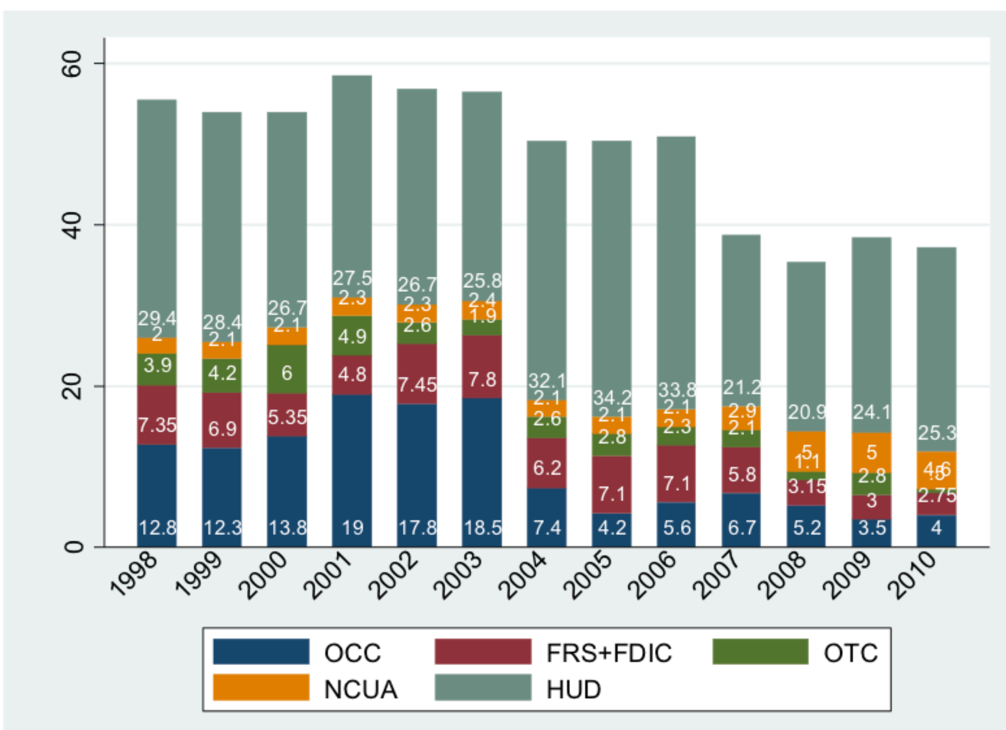
	Matched Sample	Unmatched Sample
Observations	4911	4133
Asset (million $)	1574	446
Deposit (million $)	935	200
# of branches	15.1	2.7
# of counties	4	1.5
Mortgage (millions $)	518	95
% of branches in MSA	77.50	19.00
% of deposits in MSA	76.70	18.80

Figure 6: Percentage of Deposit of Unmatched – SOD and HMDA Samples

(a) Unmatched SOD



(b) Unmatched HMDA



9.2 System of equations for demand derivatives

In this Appendix, we derive the expressions for the price derivatives of demand equations $s_{jm}^{d} = f_{jm}^{d}\left(\mathbf{p}_{j}^{d}, \mathbf{p}_{j}^{\ell}\right)$ and $s_{jm}^{\ell} = f_{jm}^{\ell}\left(\mathbf{p}_{j}^{d}, \mathbf{p}_{j}^{\ell}\right)$ as the solution of a system of equations that depends on the price derivatives of the original structural demand equations $s_{jm}^{\ell} = \ell_{jm}(p_{jm}^{\ell}, s_{jm}^{d}, Q_{j}^{d})$ and $s_{jm}^{d} = d_{jm}(p_{jm}^{d}, s_{jm}^{\ell}, Q_{j}^{d})$. These price derivatives play a key role in the equilibrium conditions of the model. We derive the solution for our logit model. Since the derivation of the price derivatives for our logit model is quite involved, we first present the results for two simplified versions of our model: (a) a model with only one geographic market; that is, $\beta_{Q}^{\ell} = \beta_{Q}^{d} = 0$ and unrestricted β_{d}^{ℓ} and β_{ℓ}^{d}; and (b) a model with multiple geographic markets but without local spillovers between deposits and loans; that is, $\beta_{d}^{\ell} = \beta_{\ell}^{d} = 0$ and unrestricted β_{Q}^{ℓ} and β_{Q}^{d}). We conclude with (c) the complete model with unrestricted values for β_{d}^{ℓ}, β_{ℓ}^{d}, β_{Q}^{ℓ} and β_{Q}^{d}.

For simplicity and compactness, we use the following notation. For any bank j and any pair of markets m' and m, we have that $\Delta_{j,m',m}^{\ell\ell} \equiv \dfrac{\partial f_{jm'}^{\ell}}{\partial p_{jm}^{\ell}}$, $\Delta_{j,m',m}^{d\ell} \equiv \dfrac{\partial f_{jm'}^{d}}{\partial p_{jm}^{\ell}}$, $\Delta_{j,m',m}^{\ell d} \equiv \dfrac{\partial f_{jm'}^{\ell}}{\partial p_{jm}^{d}}$, and $\Delta_{j,m',m}^{dd} \equiv \dfrac{\partial f_{jm'}^{d}}{\partial p_{jm}^{d}}$.

General demand model. Taking into account that $s_{jm}^{\ell} = \ell_{jm}(p_{jm}^{\ell}, s_{jm}^{d}, Q_{j}^{d})$ and $s_{jm}^{d} = d_{jm}(p_{jm}^{d}, s_{jm}^{\ell}, Q_{j}^{d})$, we have the following system of equations:

$$
\begin{aligned}
\Delta_{j,m',m}^{\ell\ell} &= 1\{m' = m\} \left[\frac{\partial \ell_{jm}}{\partial p_{jm}^{\ell}} + \frac{\partial \ell_{jm}}{\partial s_{jm}^{d}}\, \Delta_{j,m,m}^{d\ell}\right] + \frac{\partial \ell_{jm'}}{\partial Q_{j}^{d}} \left[\sum_{\tilde{m} \in \mathcal{M}_{j}^{d}} \Delta_{j,\tilde{m},m}^{d\ell}\right] \\
\Delta_{j,m',m}^{\ell d} &= 1\{m' = m\} \left[\frac{\partial \ell_{jm}}{\partial s_{jm}^{\ell}}\, \Delta_{j,m,m}^{dd}\right] + \frac{\partial \ell_{jm'}}{\partial Q_{j}^{d}} \left[\sum_{\tilde{m} \in \mathcal{M}_{j}^{d}} \Delta_{j,\tilde{m},m}^{dd}\right] \\
\Delta_{j,m',m}^{dd} &= 1\{m' \neq m\} \left[\frac{\partial d_{jm}}{\partial p_{jm}^{d}} + \frac{\partial d_{jm}}{\partial s_{jm}^{\ell}}\, \Delta_{j,m,m}^{\ell d}\right] + \frac{\partial d_{jm'}}{\partial Q_{j}^{d}} \left[\sum_{\tilde{m} \in \mathcal{M}_{j}^{d}} \Delta_{j,\tilde{m},m}^{dd}\right] \\
\Delta_{j,m',m}^{d\ell} &= 1\{m' \neq m\} \left[\frac{\partial d_{jm}}{\partial s_{jm}^{\ell}}\, \Delta_{j,m,m}^{\ell\ell}\right] + \frac{\partial d_{jm'}}{\partial Q_{j}^{d}} \left[\sum_{\tilde{m} \in \mathcal{M}_{j}^{d}} \Delta_{j,\tilde{m},m}^{d\ell}\right]
\end{aligned}
\tag{A.1}
$$

This is a system of linear equations in the vector of partial derivatives $\{\Delta_{j,m',m}^{\ell\ell}$, $\Delta_{j,m',m}^{\ell d}$, $\Delta_{j,m',m}^{d\ell}$, $\Delta_{j,m',m}^{dd}$: for $m' \in \mathcal{M}_{j}\}$, where $\mathcal{M}_{j} \equiv \mathcal{M}_{j}^{d} \cup \mathcal{M}_{j}^{\ell}$. Solving this linear system we can obtain this vector in terms of the derivatives of the structural demand functions ℓ_{jm} and d_{jm}. The solution to this system implicitly implies the existence of local and global multiplier effects to the changes in local interest rates.

(a) Model with one geographic market. The demand equations are given by logit models where the utility of purchasing the loan product of bank j for the average consumer is $-\alpha_\ell \; p^\ell_{jm} + \beta^\ell_d \; s^d_{jm} + \xi^\ell_{jm}$, where for notational simplicity here we use ξ^ℓ_{jm} to represent the sum of all the exogenous variables affecting demand, e.g., number of branches. Similarly, the utility of purchasing the deposit product of bank j is $-\alpha_d \; p^d_{jm} + \beta^d_\ell \; s^\ell_{jm} + \xi^d_{jm}$. For notational simplicity, we omit the bank subindex j from the expressions below, since this index is not necessary here.

Since $\beta^\ell_Q = \beta^d_Q = 0$, we have that $\partial \ell_m / \partial Q^d = 0$ and $\partial d_m / \partial Q^d = 0$. The logit model implies that $\partial \ell_m / \partial p^\ell_m = -\alpha_\ell \; s^\ell_m \left(1 - s^\ell_m\right)$, $\partial d_m / \partial p^d_m = -\alpha_d \; s^d_m \left(1 - s^d_m\right)$, $\partial \ell_m / \partial s^d_m = \beta^\ell_d \; s^\ell_m \left(1 - s^\ell_m\right)$, and $\partial d_m / \partial s^\ell_m = \beta^d_\ell \; s^d_m \left(1 - s^d_m\right)$. Therefore, equation (A.1) becomes:

$$
\begin{aligned}
\Delta^{\ell\ell}_{m,m} &= s^\ell_m \left(1 - s^\ell_m\right) \; \left[-\alpha_\ell + \beta^\ell_d \; \Delta^{d\ell}_{m,m}\right] \\
\Delta^{\ell d}_{m,m} &= s^\ell_m \left(1 - s^\ell_m\right) \; \beta^\ell_d \; \Delta^{dd}_{m,m} \\
\Delta^{dd}_{m,m} &= s^d_m \left(1 - s^d_m\right) \; \left[-\alpha_d + \beta^d_\ell \; \Delta^{\ell d}_{m,m}\right] \\
\Delta^{d\ell}_{m,m} &= s^d_m \left(1 - s^d_m\right) \; \beta^d_\ell \; \Delta^{\ell\ell}_{m,m}
\end{aligned}
\tag{A.2}
$$

Solving for the total derivatives in this system of equations, we obtain:

$$
\begin{aligned}
\Delta^{\ell\ell}_{m,m} &= \frac{1}{\delta_m} \; \left[-\alpha_\ell \; s^\ell_m \left(1 - s^\ell_m\right)\right] \\
\Delta^{\ell d}_{m,m} &= \frac{1}{\delta_m} \; \left[-\alpha_\ell \; \beta^\ell_d \; s^\ell_m \left(1 - s^\ell_m\right) \; s^d_m \left(1 - s^d_m\right)\right] \\
\Delta^{dd}_{m,m} &= \frac{1}{\delta_m} \; \left[-\alpha_d \; s^d_m \left(1 - s^d_m\right)\right] \\
\Delta^{d\ell}_{m,m} &= \frac{1}{\delta^*} \; \left[-\alpha_d \; \beta^d_\ell \; s^\ell_m \left(1 - s^\ell_m\right) \; s^d_m \left(1 - s^d_m\right)\right]
\end{aligned}
\tag{A.3}
$$

where $\delta_m \equiv 1 - \beta^\ell_d \; \beta^d_\ell \; s^\ell_m \left(1 - s^\ell_m\right) \; s^d_m \left(1 - s^d_m\right)$. Note that the total derivatives $\Delta^{\ell\ell}_{m,m}$ and $\Delta^{dd}_{m,m}$ are equal to the corresponding demand-price derivatives in the model with spillovers (that is, $-\alpha_\ell \; s^\ell_m \left(1 - s^\ell_m\right)$ and $-\alpha_d \; s^d_m \left(1 - s^d_m\right)$, respectively) multiplied by $\dfrac{1}{\delta_m}$. Therefore, the term $\dfrac{1}{\delta_m}$ can be interpreted as a *multiplier* associated with the spillover effect.

(b) Model with multiple geographic markets but without local spillovers between deposits and loans. The demand equations are logit models where the utility of purchasing the loan product of bank j in market m is $-\alpha_\ell \; p^\ell_{jm} + \beta^\ell_Q \; \ln Q^d_j + \xi^\ell_{jm}$, and the utility of purchasing the deposit product of bank j is $-\alpha_d \; p^d_{jm} + \beta^d_Q \; \ln Q^d_j + \xi^d_{jm}$. For notational simplicity, we omit the bank subindex j from the expressions below, since it is not necessary.

The demand system implies the following system of equations for these total derivatives, for any pair of markets n, m:

$$\begin{aligned}
\Delta^{\ell\ell}_{m',m} &= s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)\ \left[-\alpha_{\ell}\ 1\{m' = m\} + \widetilde{\beta}^{\ell}_{Q}\ \Sigma^{d\ell}_{m}\right] \\
\Delta^{\ell d}_{m',m} &= s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)\ \widetilde{\beta}^{\ell}_{Q}\ \Sigma^{dd}_{m} \\
\Delta^{dd}_{m',m} &= s^{d}_{m'}\left(1 - s^{d}_{m'}\right)\ \left[-\alpha_{d}\ 1\{m' = m\} + \widetilde{\beta}^{d}_{Q}\ \Sigma^{dd}_{m}\right] \\
\Delta^{d\ell}_{m',m} &= s^{d}_{m'}\left(1 - s^{d}_{m'}\right)\ \widetilde{\beta}^{d}_{Q}\ \Sigma^{d\ell}_{m}
\end{aligned} \tag{A.4}$$

where $\widetilde{\beta}^{\ell}_{Q} \equiv \beta^{\ell}_{Q}/Q^{d}$, $\widetilde{\beta}^{d}_{Q} \equiv \beta^{d}_{Q}/Q^{d}$, $\Sigma^{d\ell}_{m} \equiv \sum_{m'=1}^{M} \Delta^{d\ell}_{m',m}$, and $\Sigma^{dd}_{m} \equiv \sum_{m'=1}^{M} \Delta^{dd}_{m',m}$. Using the equation for $\Delta^{d\ell}_{m',m}$, we can aggregate over markets m' in both sides of the equation, and the resulting equation shows that $\Sigma^{d\ell}_{m} = 0$. This also implies that $\Delta^{d\ell}_{m',m} = 0$ for any pair m', m. This is quite intuitive: since there are not spillover effects from loans to deposits, a change in the price of loan in market m does to have any effect on the demand of deposits at any market. Plugging this result into the equation for $\Delta^{\ell\ell}_{m',m}$, we obtain that $\Delta^{\ell\ell}_{m',m} = -\alpha_{\ell}\ 1\{m' = m\}\ s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)$. That is, the own price derivative in the demand for loans has the same expression as in a model without spillovers.

Similarly, using the equation for $\Delta^{dd}_{m',m}$, we can aggregate over markets m' in both sides of the equation and solve for Σ^{dd}_{m} to obtain that $\Sigma^{dd}_{m} = \dfrac{-\alpha_{d}}{\Lambda} s^{d}_{m}\left(1 - s^{d}_{m}\right)$, with $\Lambda \equiv 1 - \widetilde{\beta}^{d}_{Q} \sum_{m'=1}^{M} s^{d}_{m'}\left(1 - s^{d}_{m'}\right)$. The term $\dfrac{1}{\Lambda}$ can be interpreted as a multiplier associated to the spillover effects. Plugging this result into the equation for $\Delta^{\ell d}_{m',m}$, we obtain that $\Delta^{\ell d}_{m',m} = \dfrac{-\alpha_{d}}{\Lambda}\ \widetilde{\beta}^{\ell}_{Q}\ s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)\ s^{d}_{m}\left(1 - s^{d}_{m}\right)$. The following expressions summarize the solution for the total derivatives in the demand system of equations:

$$\begin{aligned}
\Delta^{\ell\ell}_{m',m} &= -\alpha_{\ell}\ s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)\ 1\{m' = m\} \\
\Delta^{\ell d}_{m',m} &= -\alpha_{d}\ \frac{\widetilde{\beta}^{\ell}_{Q}}{\Lambda}\ s^{\ell}_{m'}\left(1 - s^{\ell}_{m'}\right)\ s^{d}_{m}\left(1 - s^{d}_{m}\right) \\
\Delta^{dd}_{m',m} &= -\alpha_{d}\ s^{d}_{m'}\left(1 - s^{d}_{m'}\right)\ 1\{m' = m\} - \alpha_{d}\ \frac{\widetilde{\beta}^{d}_{Q}}{\Lambda}\ s^{d}_{m'}\left(1 - s^{d}_{m'}\right)\ s^{d}_{m}\left(1 - s^{d}_{m}\right) \\
\Delta^{d\ell}_{m',m} &= 0
\end{aligned} \tag{A.5}$$

(c) Model with both local and global spillover effects. The model where all the parameters (β^{d}_{ℓ}, β^{ℓ}_{d}, β^{d}_{Q}, β^{ℓ}_{Q}) are unrestricted is a generalization of the previous models.

Now, the system of equations for the total derivatives is:

$$
\begin{aligned}
\Delta^{\ell\ell}_{m',m} &= s^{\ell}_{m'}\left(1-s^{\ell}_{m'}\right)\ \left[\left[-\alpha_{\ell}+\beta^{\ell}_{d}\ \Delta^{d\ell}_{m,m}\right]\ 1\{m'=m\}+\widetilde{\beta}^{\ell}_{Q}\ \Sigma^{d\ell}_{m}\right] \\
\Delta^{\ell d}_{m',m} &= s^{\ell}_{m'}\left(1-s^{\ell}_{m'}\right)\ \left[\beta^{\ell}_{d}\ \Delta^{dd}_{m,m}\ 1\{m'=m\}+\widetilde{\beta}^{\ell}_{Q}\ \Sigma^{dd}_{m}\right] \\
\Delta^{dd}_{m',m} &= s^{d}_{m'}\left(1-s^{d}_{m'}\right)\ \left[\left[-\alpha_{d}+\beta^{d}_{\ell}\ \Delta^{\ell d}_{m,m}\right]\ 1\{m'=m\}+\widetilde{\beta}^{d}_{Q}\ \Sigma^{dd}_{m}\right] \\
\Delta^{d\ell}_{m',m} &= s^{d}_{m'}\left(1-s^{d}_{m'}\right)\ \left[\beta^{d}_{\ell}\ \Delta^{\ell\ell}_{m,m}\ 1\{m'=m\}+\widetilde{\beta}^{d}_{Q}\ \Sigma^{d\ell}_{m}\right]
\end{aligned}
\tag{A.6}
$$

where $\Delta's$, $\Sigma's$, $\widetilde{\beta}^{\ell}_{Q}$, and $\widetilde{\beta}^{d}_{Q}$ have the same interpretation as above. First, consider the subsystem of two equation for $\Delta^{\ell\ell}_{m,m}$ and $\Delta^{d\ell}_{m,m}$.

$$
\begin{aligned}
\Delta^{\ell\ell}_{m,m} &= s^{\ell}_{m}\left(1-s^{\ell}_{m}\right)\ \left[-\alpha_{\ell}+\beta^{\ell}_{d}\ \Delta^{d\ell}_{m,m}+\widetilde{\beta}^{\ell}_{Q}\ \Sigma^{d\ell}_{m}\right] \\
\Delta^{d\ell}_{m,m} &= s^{d}_{m}\left(1-s^{d}_{m}\right)\ \left[\beta^{d}_{\ell}\ \Delta^{\ell\ell}_{m,m}+\widetilde{\beta}^{d}_{Q}\ \Sigma^{d\ell}_{m}\right]
\end{aligned}
\tag{A.7}
$$

We can see this as a system of two linear equations where the two unknowns are $\Delta^{\ell\ell}_{m,m}$ and $\Delta^{d\ell}_{m,m}$. Solving this system, we have that:

$$
\begin{aligned}
\Delta^{\ell\ell}_{m,m} &= \frac{1}{\delta^{*}_{m}}\left[-\alpha_{\ell}\ s^{\ell}_{m}\left(1-s^{\ell}_{m}\right)+\left(\beta^{\ell}_{Q}\ s^{\ell}_{m}\left(1-s^{\ell}_{m}\right)+\frac{\beta^{d}_{Q}}{\beta^{d}_{\ell}}\left(1-\delta^{*}_{m}\right)\right)\ \Sigma^{d\ell}_{m}\right] \\
\Delta^{d\ell}_{m,m} &= \frac{1}{\delta^{*}_{m}}\left[\frac{-\alpha_{\ell}}{\beta^{\ell}_{d}}\left(1-\delta^{*}_{m}\right)+\left(\beta^{d}_{Q}\ s^{d}_{m}\left(1-s^{d}_{m}\right)+\frac{\beta^{\ell}_{Q}}{\beta^{\ell}_{d}}\ \left(1-\delta^{*}_{m}\right)\right)\ \Sigma^{d\ell}_{m}\right]
\end{aligned}
\tag{A.8}
$$

where $\delta_{m}\equiv 1-\beta^{\ell}_{d}\ \beta^{d}_{\ell}\ s^{\ell}_{m}\left(1-s^{\ell}_{m}\right)\ s^{d}_{m}\left(1-s^{d}_{m}\right)$. Going back to the expression for $\Delta^{d\ell}_{m',m}$ in (A.6), we can aggregate over markets m' in both sides of the equation and solve for $\Sigma^{d\ell}_{m}$ to obtain that $\Sigma^{d\ell}_{m}=\dfrac{\beta^{d}_{\ell}}{\Lambda^{*}}s^{d}_{m}\left(1-s^{d}_{m}\right)\ \Delta^{\ell\ell}_{m,m}$. Plugging this result into the equation $\Delta^{\ell\ell}_{m,m}$ in (A.8), and after some algebra, we get that $\Delta^{\ell\ell}_{m,m}=\dfrac{-\alpha_{\ell}}{\lambda_{m}}s^{\ell}_{m}\left(1-s^{\ell}_{m}\right)$, where $\lambda_{m}=1-\dfrac{1-\delta_{m}}{\Lambda}$ $[\Lambda+\dfrac{\widetilde{\beta}^{\ell}_{Q}}{\widetilde{\beta}^{\ell}_{d}}+\widetilde{\beta}^{d}_{Q}\ s^{d}_{m}\left(1-s^{d}_{m}\right)]$. The term $\dfrac{1}{\lambda_{m}}$ can be interpreted as a multiplier that accounts for the combined effect of local and global spillovers. Plugging back this expression for $\Delta^{\ell\ell}_{m,m}$ into $\Sigma^{d\ell}_{m}$ we obtain that $\Sigma^{d\ell}_{m}=\dfrac{-\alpha_{\ell}}{\beta^{\ell}_{d}}\dfrac{1-\delta_{m}}{\lambda_{m}\Lambda}$. And using this expression into the equation for $\Delta^{d\ell}_{m,m}$ in (A.8), we get that $\Delta^{d\ell}_{m,m}=\dfrac{-\alpha_{\ell}}{\beta^{\ell}_{d}}\dfrac{1-\delta_{m}}{\lambda_{m}\Lambda}[\Lambda+\beta^{d}_{Q}s^{d}_{m}\left(1-s^{d}_{m}\right)]$. In summary, the solution for $\Delta^{\ell\ell}_{m,m}$, $\Delta^{d\ell}_{m,m}$, and $\Sigma^{d\ell}_{m}$ is:

$$
\begin{aligned}
\Delta^{\ell\ell}_{m,m} &= -\alpha_\ell \; s^\ell_m \left(1 - s^\ell_m\right) \; \frac{1}{\lambda_m} \\
\Delta^{d\ell}_{m,m} &= \frac{-\alpha_\ell}{\beta^\ell_d} \frac{1-\delta_m}{\Lambda\lambda_m} \; \left[\Lambda + \widetilde{\beta}^d_Q s^d_m \left(1 - s^d_m\right)\right] \\
\Sigma^{d\ell}_{m} &= \frac{-\alpha_\ell}{\beta^\ell_d} \frac{1-\delta_m}{\Lambda\lambda_m}
\end{aligned}
\tag{A.9}
$$

Taking into account the expressions for $\Delta^{d\ell}_{m',m}$ and $\Delta^{d\ell}_{m',m}$ in (A.13), we can that see given $\Delta^{\ell\ell}_{m,m}$, $\Delta^{dd}_{m,m}$, and $\Sigma^{d\ell}_{m}$ we can obtain all the derivatives for any pair m', m.

Now, we proceed similarly with the total derivatives $\Delta^{\ell d}_{m',m}$ and $\Delta^{dd}_{m',m}$. First, we consider the subsystem of two equations for $\Delta^{\ell d}_{m,m}$ and $\Delta^{dd}_{m,m}$.

$$
\begin{aligned}
\Delta^{\ell d}_{m,m} &= s^\ell_m \left(1 - s^\ell_m\right) \; \left[\beta^\ell_d \; \Delta^{dd}_{m,m} + \widetilde{\beta}^\ell_Q \; \Sigma^{dd}_m\right] \\
\Delta^{dd}_{m,m} &= s^d_m \left(1 - s^d_m\right) \; \left[-\alpha_d + \beta^d_\ell \; \Delta^{\ell d}_{m,m} + \widetilde{\beta}^d_Q \; \Sigma^{dd}_m\right]
\end{aligned}
\tag{A.10}
$$

Solving for $\Delta^{dd}_{m,m}$ and $\Delta^{\ell d}_{m,m}$ in this system, we have that:

$$
\begin{aligned}
\Delta^{dd}_{m,m} &= \frac{1}{\delta_m} \left[-\alpha_d \; s^d_m \left(1 - s^d_m\right) + \left(\widetilde{\beta}^d_Q \; s^d_m \left(1 - s^d_m\right) + \frac{\widetilde{\beta}^\ell_Q}{\beta^\ell_d}(1-\delta_m)\right) \; \Sigma^{dd}_m\right] \\
\Delta^{\ell d}_{m,m} &= \frac{1}{\delta_m} \left[\frac{-\alpha_d}{\beta^d_\ell}(1-\delta_m) + \left(\widetilde{\beta}^\ell_Q \; s^\ell_m \left(1 - s^\ell_m\right) + \frac{\widetilde{\beta}^d_Q}{\widetilde{\beta}^d_\ell} \; (1-\delta_m)\right) \; \Sigma^{dd}_m\right]
\end{aligned}
\tag{A.11}
$$

Going back to the expression for $\Delta^{dd}_{m',m}$ (A.6), we can aggregate over markets n in both sides of the equation and solve for Σ^{dd}_m to obtain that $\Sigma^{dd}_m = \frac{1}{\Lambda}[-\alpha_d + \beta^d_\ell \; \Delta^{\ell d}_{m,m}] \; s^d_m \left(1 - s^d_m\right)$. Plugging this result into the equation for $\Delta^{\ell d}_{m,m}$ in (A.11), solving for $\Delta^{\ell d}_{m,m}$, and after some algebra, we get that $\Delta^{\ell d}_{m,m} = \frac{-\alpha_d}{\beta^d_\ell} \; \frac{1-\lambda_m}{\lambda_m}$. Plugging back this expression into Σ^{dd}_m we obtain that $\Sigma^{dd}_m = -\alpha_d \; s^d_m \left(1 - s^d_m\right) \; \frac{1}{\Lambda\lambda_m}$. And plugging this into the equation for $\Delta^{dd}_{m,m}$ in (A.11), and after some algebra, we get $\Delta^{dd}_{m,m} = -\alpha_d \; s^d_m \left(1 - s^d_m\right) \; \frac{1}{\delta_m}$. In summary, the solution for

$\Delta^{dd}_{m,m}$, $\Delta^{\ell d}_{m,m}$, and Σ^{dd}_{m} is:

$$\begin{aligned}
\Delta^{dd}_{m,m} &= -\alpha_d \; s^d_m \left(1 - s^d_m\right) \; \frac{1}{\delta_m} \\
\Delta^{\ell d}_{m,m} &= \frac{-\alpha_d}{\beta^d_\ell} \frac{1-\lambda_m}{\lambda_m} \\
\Sigma^{dd}_{m} &= -\alpha_d \; s^d_m \left(1 - s^d_m\right) \frac{1}{\Lambda \lambda_m}
\end{aligned} \tag{A.12}$$

Taking into account the expressions for $\Delta^{\ell d}_{m',m}$ and $\Delta^{dd}_{m',m}$ in (A.6), we can see that given $\Delta^{dd}_{m,m}$, $\Delta^{\ell d}_{m,m}$, and Σ^{dd}_{m} we can obtain all the derivatives for any pair m', m.

9.3 Best-response pricing equations

In this Appendix, we derive the expression for the best-response pricing equations that we use in section 3.3 to obtain the system of equilibrium equations. As above, to facilitate the description of this derivation, we start presenting the result for two simplified versions of the model: (a) a model with only one geographic market; that is, $\beta_Q^\ell = \beta_Q^d = 0$ and unrestricted β_d^ℓ and β_ℓ^d; and (b) a model with multiple geographic markets but without local spillovers between deposits and loans; that is, $\beta_d^\ell = \beta_\ell^d = 0$ and unrestricted β_Q^ℓ and β_Q^d). We conclude with (c) the complete model with unrestricted values for β_d^ℓ, β_ℓ^d, β_Q^ℓ and β_Q^d.

(a) Model with one geographic market. The profit function of bank j in market m is $p_{jm}^\ell \; q_{jm}^\ell + p_{jm}^d \; q_{jm}^d - \widetilde{C}_{jm}\left(q_{jm}^\ell, q_{jm}^d\right)$. For notational simplicity, we omit the bank subindex j from the expressions below, since this index is not necessary here. The first order conditions for the profit maximization of a bank are:

$$\left\{ \begin{array}{lcl} s_m^\ell + \left(p_m^\ell - c_m^\ell\right) \; \Delta_{m,m}^{\ell\ell} + \left(p_m^d - c_m^d\right) \; \Delta_{m,m}^{d\ell} & = & 0 \\ \\ s_m^d + \left(p_m^\ell - c_m^\ell\right) \; \Delta_{m,m}^{\ell d} + \left(p_m^d - c_m^d\right) \; \Delta_{m,m}^{dd} & = & 0 \end{array} \right. \tag{A.13}$$

Using the expressions for the $\Delta's$ that we have obtained in equation (A.3) and plugging them into the first order conditions of optimality, we obtain:

$$\left\{ \begin{array}{lcl} s_m^\ell - \left(p_m^\ell - c_m^\ell\right) \; \dfrac{1}{\delta_m} \; \alpha_\ell \; s_m^\ell \left(1 - s_m^\ell\right) - \left(p_m^d - c_m^d\right) \; \left(\dfrac{1-\delta_m}{\delta_m}\right) \; \dfrac{\alpha_d}{\beta_d^\ell} & = & 0 \\ \\ s_m^d - \left(p_m^\ell - c_m^\ell\right) \; \left(\dfrac{1-\delta_m}{\delta_m}\right) \; \dfrac{\alpha_\ell}{\beta_\ell^d} - \left(p_m^d - c_m^d\right) \; \dfrac{1}{\delta_m} \alpha_d \; s_m^d \left(1 - s_m^d\right) & = & 0 \end{array} \right. \tag{A.14}$$

Combining these two conditions, and after some algebra, we can obtain the following expression for the best response price-cost margins:

$$\left\{ \begin{array}{lcl} p_m^\ell - c_m^\ell & = & \dfrac{1}{\alpha_\ell (1 - s_m^\ell)} - \dfrac{\beta_\ell^d}{\alpha_d} \; s_m^d \\ \\ p_m^d - c_m^d & = & \dfrac{1}{\alpha_d (1 - s_m^d)} - \dfrac{\beta_d^\ell}{\alpha_\ell} \; s_m^\ell \end{array} \right. \tag{A.15}$$

Comparing the expressions in (A.15) with the price-cost margins in a standard logit model of Bertrand competition (when $\beta_\ell^d = \beta_d^\ell = 0$), we can see that the spillover effects in the demands for loans and deposits generate an incentive to reduce price-cost margins in the two markets. The effect of the demand spillover on the price-cost margin, $-\dfrac{\beta_\ell^d}{\alpha_d} \; s_m^d$ and $-\dfrac{\beta_d^\ell}{\alpha_\ell} \; s_m^\ell$, has exactly the same magnitude as the direct spillover effect on a consumer's willingness to pay for the product.

(b) Model with multiple geographic markets but without local spillovers between deposits and loans. The profit function of bank j is $\sum_{m=1}^M p_{jm}^\ell \; q_{jm}^\ell + \sum_{m=1}^M p_{jm}^d \; q_{jm}^d -$

$\widetilde{C}_{jm}\left(q_{jm}^{\ell}, q_{jm}^{d}\right)$. For notational simplicity, we omit the bank subindex j from the expressions below, since it is not necessary. The first order conditions for the profit maximization of a bank are, for any market m:

$$\left\{\begin{array}{rcl} s_m^{\ell} + \sum_{m'=1}^{M}\left(p_{m'}^{\ell} - c_{m'}^{\ell}\right)\ \Delta_{m',m}^{\ell\ell} + \sum_{m'=1}^{M}\left(p_{m'}^{d} - c_{m'}^{d}\right)\ \Delta_{m',m}^{d\ell} & = & 0 \\ s_m^{d} + \sum_{m'=1}^{M}\left(p_{m'}^{\ell} - c_{m'}^{\ell}\right)\ \Delta_{m',m}^{\ell d} + \sum_{m'=1}^{M}\left(p_{m'}^{d} - c_{m'}^{d}\right)\ \Delta_{m',m}^{dd} & = & 0 \end{array}\right. \tag{A.16}$$

Using the expressions for the $\Delta' s$ that we have obtained in equation (A.5) and plugging them into the first order conditions of optimality, we obtain:

$$\left\{\begin{array}{rcl} s_m^{\ell} - \alpha_\ell\ \left(p_m^{\ell} - c_m^{\ell}\right)\ s_m^{\ell}\left(1 - s_m^{\ell}\right) & = & 0 \\ s_m^{d} - \alpha_d\ \left(p_m^{d} - c_m^{d}\right)\ s_m^{d}\left(1 - s_m^{d}\right) - \dfrac{1}{\Lambda}\ \alpha_d\ s_m^{d}\left(1 - s_m^{d}\right)\left[\widetilde{\beta}_Q^{\ell}\ PCM_\ell + \widetilde{\beta}_Q^{d}\ PCM_d\right] & = & 0 \end{array}\right. \tag{A.17}$$

with $PCM_\ell \equiv \sum_{m'=1}^{M}\left(p_{m'}^{\ell} - c_{m'}^{\ell}\right) s_{m'}^{\ell}\left(1 - s_{m'}^{\ell}\right)$ and $PCM_d \equiv \sum_{m'=1}^{M}\left(p_{m'}^{d} - c_{m'}^{d}\right) s_{m'}^{d}\left(1 - s_{m'}^{d}\right)$. We can see that the first order conditions with respect to the price of loans imply the same pricing equations as in the standard logit model of Bertrand competition:

$$p_m^{\ell} - c_m^{\ell} \quad = \quad \frac{1}{\alpha_\ell(1 - s_m^{\ell})} \tag{A.18}$$

That is, since the bank's aggregate loans does not have any spillover effects on the demand of loans or deposits, the pricing of loans does not have to internalize any spillover effect. This implies that $PCM_\ell \equiv Q_\ell/\alpha_\ell$. The first order conditions with respect to the prices of deposits imply the pricing equation:

$$p_m^{d} - c_m^{d} \quad = \quad \frac{1}{\alpha_d(1 - s_m^{d})} - \frac{1}{\Lambda}\left[\widetilde{\beta}_Q^{\ell}\ \frac{Q_\ell}{\alpha_\ell} + \widetilde{\beta}_Q^{d}\ PCM_d\right] \tag{A.19}$$

Multiplying this equation times $s_m^d(1-s_m^d)$, aggregating over markets, and taking into account that $\sum_{m=1}^{M} s_m^d(1 - s_m^d) = (1 - \Lambda)/\widetilde{\beta}_Q^{d}$, we have solve for PCM_d to obtain that $PCM_d = \Lambda$ $[1 - \dfrac{1-\Lambda}{\Lambda}\ \dfrac{\widetilde{\beta}_Q^{\ell}}{\widetilde{\beta}_Q^{d}}]\ \dfrac{Q_\ell}{\alpha_\ell}$, and this implies that $\widetilde{\beta}_Q^{\ell}\ \dfrac{Q_\ell}{\alpha_\ell} + \widetilde{\beta}_Q^{d}\ PCM_d = \Lambda\ (\widetilde{\beta}_Q^{d} + \widetilde{\beta}_Q^{\ell})\dfrac{Q_\ell}{\alpha_\ell}$. Solving this expression into equation (A.11), and taking into account that $\widetilde{\beta}_Q^{\ell} \equiv \beta_Q^{\ell}/Q^d$ and $\widetilde{\beta}_Q^{d} \equiv \beta_Q^{d}/Q^d$, we get:

$$p_m^{d} - c_m^{d} \quad = \quad \frac{1}{\alpha_d(1 - s_m^{d})} - \frac{\beta_Q^{d} + \beta_Q^{\ell}}{\alpha_\ell}\frac{Q_\ell}{Q_d} \tag{A.20}$$

Comparing this expression with the price-cost margins in a standard logit model of Bertrand competition (when $\beta_Q^d = \beta_Q^\ell = 0$), we can see that the spillover effect from the bank's total deposits generates an incentive to reduce the price-cost margin in the deposit market.

(c) Model with both local and global spillover effects. The model where all the parameters $(\beta_\ell^d,\ \beta_d^\ell,\ \beta_Q^d,\ \beta_Q^\ell)$ are unrestricted is a generalization of the previous models.

Though the algebra and the expressions are more involved, it turns out that the expressions for the pricing equations are a natural and intuitive extension of the pricing equations in the previous simpler models.

The first order conditions have the same form as in (A.16). We can write these conditions as:

$$\left\{ \begin{array}{lcl} s_m^\ell + \left(p_m^\ell - c_m^\ell\right) \; s_m^\ell \left(1 - s_m^\ell\right) \; \left[-\alpha_\ell + \beta_d^\ell \; \Delta_{m,m}^{d\ell}\right] + \left[\beta_Q^\ell \; PCM_\ell + \beta_Q^d \; PCM_d\right] \; \Sigma_m^{d\ell} \\ \qquad + \left(p_m^d - c_m^d\right) \; s_m^d \left(1 - s_m^d\right) \; \beta_\ell^d \; \Delta_{m,m}^{\ell\ell} & = & 0 \\ \\ s_m^d + \left(p_m^\ell - c_m^\ell\right) \; s_m^\ell \left(1 - s_m^\ell\right) \; \beta_d^\ell \; \Delta_{m,m}^{dd} + \left[\beta_Q^\ell \; PCM_\ell + \beta_Q^d \; PCM_d\right] \; \Sigma_m^{dd} \\ \qquad + \left(p_m^d - c_m^d\right) \; s_m^d \left(1 - s_m^d\right) \; \left[-\alpha_d + \beta_\ell^d \; \Delta_{m,m}^{\ell d}\right] & = & 0 \end{array} \right. \tag{A.21}$$

where PCM_ℓ and PCM_d have the same definition as above. Using the expressions for the $\Delta' s$ that we have obtained in equation (A.9) and (A.12), and plugging them into the first order conditions of optimality, we obtain:

$$\left\{ \begin{array}{lcl} s_m^\ell - \alpha_\ell \; \left(p_m^\ell - c_m^\ell\right) \; s_m^\ell \left(1 - s_m^\ell\right) \; \left[\dfrac{\Lambda - (1-\delta_m)\widetilde{\beta}_Q^\ell / \beta_d^\ell}{\Lambda \lambda_m}\right] \\ + \left[\widetilde{\beta}_Q^\ell \; PCM_\ell + \widetilde{\beta}_Q^d \; PCM_d\right] \; \left[\dfrac{-\alpha_\ell}{\beta_d^\ell} \dfrac{1-\delta_m}{\Lambda \lambda_m}\right] - \dfrac{\alpha_\ell}{\beta_d^\ell} \; \left(p_m^d - c_m^d\right) \; \dfrac{1-\delta_m}{\lambda_m} & = & 0 \\ \\ s_m^d - \dfrac{\alpha_d}{\beta_\ell^d} \; \left(p_m^\ell - c_m^\ell\right) \; \dfrac{1-\delta_m}{\delta_m} - \alpha_d \; s_m^d \left(1 - s_m^d\right) \dfrac{1}{\Lambda \lambda_m} \left[\widetilde{\beta}_Q^\ell \; PCM_\ell + \widetilde{\beta}_Q^d \; PCM_d\right] \\ \qquad -\alpha_d \; \left(p_m^d - c_m^d\right) \; s_m^d \left(1 - s_m^d\right) \dfrac{1}{\lambda_m} & = & 0 \end{array} \right. \tag{A.22}$$

Given these equations, we can follow a similar approach as for the model in (b). First, we aggregate these equations over markets and solve for $\widetilde{\beta}_Q^\ell \; PCM_\ell + \widetilde{\beta}_Q^d \; PCM_d$. And finally we solve for the price-cost margins $p_m^\ell - c_m^\ell$ and $p_m^d - c_m^d$ to obtain the following expressions:

$$\left\{ \begin{array}{lcl} p_m^\ell - c_m^\ell & = & \dfrac{1}{\alpha_\ell (1 - s_m^\ell)} - \dfrac{\beta_\ell^d}{\alpha_d} \; s_m^d \\ \\ p_m^d - c_m^d & = & \dfrac{1}{\alpha_d (1 - s_m^d)} - \dfrac{\beta_\ell^d}{\alpha_d} \; s_m^d - \dfrac{\beta_Q^d + \beta_Q^\ell}{\alpha_\ell} \dfrac{Q_\ell}{Q_d} \end{array} \right. \tag{A.23}$$