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The Geographic Flow of Bank Funding and Access to Credit: Branch Networks and Local-Market Competition

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Abstract

This paper studies the integration of deposit and loan markets, which may be constrained by the geographic dispersion of depositors, borrowers, and banks. This dispersion results in problems of asymmetric information, monitoring and transaction costs, which in turn may prevent deposits from flowing from areas of low demand for loans to areas of high demand. We provide systematic evidence on the extent to which deposits and loans are geographically imbalanced, and develop a methodology for investigating the contribution of (i) branch networks, (ii) local market power, and (iii) economies of scope to this imbalance using data at the bank-county-year level from the US banking industry for 1998-2010. Our results are based on the construction of an index which measures the geographic imbalance of deposits and loans, and the estimation of a structural model of bank oligopoly competition for deposits and loans in multiple geographic markets. The estimated model shows that a bank's total deposits have a significant effect on the bank's market shares in loan markets. We also find evidence of significant economies of scope between deposits and loans at the local level. 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 has a very substantial negative effect on the flow of credit to smaller/poorer counties.

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

There is evidence that heterogeneity exists in the ability of individuals to access credit. Since access to financing has been linked to entrepreneurship levels, employment, wages, and economic growth (see for instance Gine and Townsend (2004)), this heterogeneity can lead to socio-economic inequality. Moreover, there is mounting concern among policy makers that differences in the ability to access loans is at least partly geographic, with individuals in some regions able to more easily obtain financing than individuals in other regions.[1]

An important determinant of credit provision is the availability of deposits: greater deposits allow banks to make more loans (Jayaratne and Morgan, 2000). Unfortunately, in any given region, the demand for loans may not always coincide with the availability of deposits. This would not be a problem in an economy without geographic frictions, as funds would flow from one area to another such that, in equilibrium, the expected rate of return and the risk of the marginal loan would be the same across geographic markets, and the funding of an investment project would not depend on its geographic location. In actual economies, geographic distance between borrowers and lenders can increase asymmetric information, monitoring costs, and transaction costs of liquidity within banks. All these can serve as frictions to the flow of funds across markets and can generate substantial geographic imbalances in the provision of, and access to, credit (*credit deserts*).[2]

Wholesale liquidity markets and bank branch networks can help to alleviate the effects of these frictions. Banks can buy and sell liquidity (deposits) in the interbank wholesale market. However, there are transaction costs involved in using these wholesale markets due to bank precautionary motives and liquidity hoarding (Ashcraft el al., 2011, Acharya and Merrouche, 2012). Banks can also use branching as an instrument to reduce geographic frictions in the flow of credit. By opening branches in multiple locations, a bank can reduce its geographic distance with borrowers, and therefore it can reduce frictions which are related to the geographic distance between lender and borrowers. If transaction costs between branches of the same bank are smaller than the costs of using interbank markets (Coase, 1937), then banks' branch networks may increase the flow of funding to geographic locations where credit is in greater demand.

Two counterbalancing forces can affect negatively the willingness of a bank to transfer funds between its branches: (i) economies of scope between deposits and loans at the branch level, and (ii) local market power. Clients may prefer to have their deposit account and their mortgage in the

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[1]See Getter (2015) for a review of the debate on this policy issue in the US Congress and Senate, related to the Community Reinvestment Act (CRA).

[2]Brevoort and Wolken (2009) and Nguyen (2015) show that the geographic distance between borrowers and lenders have a negative impact on the amount of credit.

same bank. For the bank, the cost of managing a deposit account and a loan may be smaller if they belong to the same client. These economies of scope between deposits and loans create incentives to concentrate lending activity in those branches with high levels of deposits, and therefore to limit the geographic flow of liquidity to markets with more need of credit.[3] Local 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. Local market power can have a negative impact on the geographic flow of credit.[4]

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. We focus on the following empirical questions: (i) How do branch networks contribute to the geographic flow of credit? More specifically, does credit in a county increase if its banks have branches in other counties with high supply of deposits? Did the geographic expansion of banks in the 1990s and 2000s affect the geographic flow of bank funds? (ii) How important is the 'home bias' generated by economies of scope between deposits and loans? and (iii) What is the contribution of local market power to the geographic distribution of bank credit?

To answer these questions 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 (Duncan and Duncan, 1955, Atkinson, 1970, White, 1983 and 1986, and Cutler et al., 1999). More recently, they have been used by Gentzkow et al. (2017) to quantify the degree of polarization in political speech in the US. We develop an index of the imbalance between deposits and loans

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[3]As we discuss in our Model section (section 4), these economies of scope between deposits and loans may be driven either by consumer demand (i.e., *one-stop banking*) or by variable costs. See also Kashyap, Rajan, and Stein (2002) and Egan, Lewellen, and Sunderam (2017) for models and empirical evidence on the positive synergies between banks' deposit and lending activities.

[4]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 characterized by a concentrated banking sector. There is also a small literature that examines how market structure and competition affects the transmission of monetary policy through the bank lending channel. See for instance Olivero, Li and Jeon (2011a, 2011b) and Adams and Amel (2005).

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.

The observed imbalance could be explained by institutional factors like thresholds on loan-to-deposit ratios imposed by the Community Reinvestment Act or reserve requirements, or alternatively by branch network limitations, economies of scope between deposits and loans, or local market power. To investigate the factors that contribute to the geographic imbalance of deposits and loans, we develop and estimate a structural model of bank oligopoly competition for deposits and loans in multiple geographic 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. We characterize an equilibrium of this multimarket oligopoly model and propose an algorithm to solve for an equilibrium.

In our model, differentiated banks sell deposit and loan products in multiple local markets (counties). The model incorporates three (endogenous) variables, which are key factors in a bank's demand and cost of loans and deposits in a local market. A first factor is the number of branches the bank has in the local market. The number of branches reduces marginal costs of lending and may generate consumer awareness and willingness to pay. A second factor is the total amount of deposits the bank has at the national level, that reduces 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. A third factor is the amount of deposits the bank has in the local market that increases consumer demand for loans and reduces the bank's marginal cost of a loan due to economies of scope in managing deposits and loans. These three factors are fundamental in the determination of the geographic flow of liquidity in the equilibrium of the model. The stronger the effect of local branches on the demand and cost of loans, the more concentrated are loan markets and this has a negative impact on the geographic diffusion of credit. Economies of scope between deposits and loans also reduce geographic flow of credit. In contrast, the effect of total bank deposits on local loans has a positive impact on the geographic diffusion of credit.

Our model builds on and extends the literature on structural models of bank competition. Neven and Röller (1999) estimate a model of bank oligopoly competition in loans in seven European countries. Their model assumes competition at the national level and it does not allow for

multiple local markets or for economies of scope between deposits and loans. Previous studies have proposed and estimated structural equilibrium models for bank deposits as a differentiated product. Dick (2008), Ho and Ishii (2011), and Honka, Hortaçsu, and Vitorino (2017) 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. Our paper extends these previous studies by: (a) incorporating demand, supply, and competition in the market for bank loans; (b) allowing for economies of scope between deposits and loans, which introduces an important link between these markets at the local level; and (c) including the effect of a bank's total liquidity on the demand and costs of deposits and loans in local markets.[5] Corbae and D'Erasmo (2013) propose and calibrate a dynamic equilibrium model of the US banking industry that incorporates Stackelberg oligopoly competition in both deposits and loans, endogenous market entry and exit, and multiple geographic markets. Our model is static and it does not endogenize bank-entry exit decisions. However, it provides a more detailed description of the geographic inter-connections between deposits and loans at the bank-county level. 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 the current paper, we extend this previous model by incorporating competition in both loans and deposits, and inter-connections between these two markets and across geographic markets. Here we also focus on competition at the intensive margin and omit the part of the model that has to do with competition at the extensive margin, i.e., opening and closing branches, and entry and exit in loans/deposits local markets.

Three sets of structural parameters or causal relationships are fundamental for the predictions of the model: (a) the effect of the number of local branches on a bank's demand and marginal cost for deposits and loans; (b) the causal relationship between deposits and loans at the local level; and (c) the effect of a bank's total deposits on the demand and marginal cost of loans. Estimation of these parameters must address endogeneity and simultaneity of the number of branches and of local and total deposits and loans. Our identification approach combines four conditions on the unobservable variables of the model: (i) a flexible fixed effects specification that includes fixed effects at the bank-county, year, county-year, and bank-year level; 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 assumption that the bank-year effects are not correlated with observable exogenous county characteristics. Under these assumptions, we

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[5]In Egan, Hortaçsu & Matvos (2017), the demand for uninsured deposits of a bank depends on the bank's total liquidity. However, their model does not incorporate demand and supply of loans and how they depend on the bank's liquidity.

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 (to instrument the bank's current number of branches in the county), lagged deposits, loans, and number of branches of competing banks in the county (to instrument the bank's current deposits and loans in the county), and the socioeconomic conditions in geographically distant counties where the bank has branches (to instrument the bank's total deposits). We use these moment conditions to obtain a GMM estimator of the structural parameters of the model, and present tests for the validity of our assumptions of no serial and spatial correlation in the residuals.

The estimation of the model provides the following results. First, the number of branches in a county increases (reduces) substantially the demand (cost) for 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 level of bank and local market. Third, the effect of a bank's total deposits on demand (cost) of loans is positive (negative) and very significant both economically and statistically. Finally, banks' internal liquidity reduces the costs 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 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 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 the home bias due to 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 banks in the loans market (i.e. the median values in the data for the number of banks in these markets). 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. Our results also suggest that neither a deposit tax or a national shock would be geographically neutral in their effect of bank credit.

We are not the first to study the relationship between retail funding and loan activity. The closest to our work is 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, 2012; Gilje, Loutskina, and Strahan, 2016; Loutskina and Strahan, 2015; Petkov, 2016; 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 4 we describe our model and in Section 5 we explain how we go about estimating it. Section 6 presents our empirical results and Section 7 describes our counterfactual experiments. Finally, Section 8 concludes.

2   Frictions and the flow of bank funding

In this section we present a framework for understanding how frictions affect the geographic allocation of bank funds. The framework presented here is more stylized than the empirical model we develop and estimate in Sections X and Y below, where we allow products to be horizontally differentiated between banks due to different product characteristics and to spatial differentiation within a local market.[6] For simplicity, here we consider a Cournot model with homogeneous banks and linear demand, in order to have closed form expressions with intuitive interpretations.

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[6]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.

2.1 Framework

Consider an economy with M geographic markets, indexed by $m \in \{1, 2, ..., M\}$, and J banks, indexed by $j \in \{1, 2, ..., J\}$. In each market, N_m banks sell deposit products to *savers*, and loan products to *investors*. Market level demands for deposits and loans are $q_m^d = a_m^d - p_m^d$ and $q_m^\ell = a_m^\ell - p_m^\ell$, respectively, where a_m^d and a_m^ℓ are exogenous demand parameters representing the maximum willingness to pay for deposits and loans, respectively.[7] For simplicity, we assume that every bank is active in both the deposits and loans markets. In the empirical model presented below we will relax this assumption and consider the actual branch networks of banks. Let q_{jm}^d and q_{jm}^ℓ be the amounts of deposits and loans, respectively, that bank j provides in market m. The cost of managing loans and deposits is $c_m^d \, q_{jm}^d + c_m^\ell \, q_{jm}^\ell$, where c_m^d and c_m^ℓ are exogenous marginal costs.

In an economy without an interbank market and without the possibility of transferring funds between branches of the same bank, a bank's balance sheet should hold at every local market. If these mechanisms do exist, then a bank may incur transaction costs. First, when $q_{jm}^\ell - q_{jm}^d \neq 0$, the bank has to pay a transaction cost of $\frac{\theta_w}{2}(q_{jm}^\ell - q_{jm}^d)$ per dollar unit. The parameter $\theta_w > 0$ measures the degree of friction in the transfer of bank funds *within banks*. The total *within* transaction costs for a bank are $\sum_{m=1}^M \frac{\theta_w}{2}(q_{jm}^\ell - q_{jm}^d)^2$. Second, if the total amounts of loans and deposits for bank j, $Q_j^\ell \equiv \sum_{m=1}^M q_{jm}^\ell$ and $Q_j^d \equiv \sum_{m=1}^M q_{jm}^d$, are different, then it incurs transaction costs to buy (if $Q_j^\ell - Q_j^d > 0$) or sell funds (if $Q_j^\ell - Q_j^d < 0$) on the interbank market. So participating in the interbank market implies a transaction cost of $\frac{\theta_b}{2}(Q_j^\ell - Q_j^d)$ per dollar unit. The parameter $\theta_b > 0$ measures the degree of frictions incurred from transferring funds *between banks*. Note that this transaction cost is in addition to expenses/revenues the bank obtains from buying or selling funds, equal to $r_0(Q_j^\ell - Q_j^d)$, where r_0 is the interbank rate (which for now we consider to be exogenous).

2.2 Equilibrium

A bank's profit function is given by:

$$\pi_j = \sum_{m=1}^M \left(p_m^\ell - c_m^\ell\right) q_{jm}^\ell + \left(p_m^d - c_m^d\right) q_{jm}^d - \frac{\theta_w}{2}\left(q_{jm}^\ell - q_{jm}^d\right) - \left[r_0 + \frac{\theta_b}{2}\left(Q_j^\ell - Q_j^d\right)\right]\left(Q_j^\ell - Q_j^d\right)$$

(1)

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[7]Note that we treat the demand for deposits in the same way as the demand for loans, i.e., consumers have to pay the price p_m^d to the bank to get one unit of the deposit product. Therefore, this price would be negative if it is the bank who pays consumers for depositing their savings in the bank.

Banks compete a la Nash-Cournot by choosing the amounts of deposits and loans for every market. In the absence of any geographic frictions the Nash-Cournot equilibrium quantities (per-bank) are:

$$q_{jm}^{\ell} = \frac{a_m^{\ell} - c_m^{\ell} - r_0}{N_m + 1}$$

$$q_{jm}^{d} = \frac{a_m^{d} - c_m^{d} + r_0}{N_m + 1}$$

(2)

We denote these frictionless equilibrium quantities as $q_m^{\ell*}$ and q_m^{d*} and note that, in the absence of frictions, markets for deposits and loans are separable. A shock in one of these markets affects the other only if it affects the interest rate in the interbank market.

Now, consider the Nash-Cournot equilibrium in the model with frictions. The first order conditions of optimality imply the following equations:

$$(2 + \theta_w)\, q_{jm}^{\ell} = \left(a_m^{\ell} - c_m^{\ell} - r_0\right) + \theta_w\, q_{jm}^{d} - q_{(-j)m}^{\ell} + \theta_b\left(Q_j^d - Q_j^\ell\right)$$

$$(2 + \theta_w)\, q_{jm}^{d} = \left(a_m^{d} - c_m^{d} + r_0\right) + \theta_w\, q_{jm}^{\ell} - q_{(-j)m}^{d} + \theta_b\left(Q_j^\ell - Q_j^d\right)$$

(3)

where $q_{(-j)m}^{\ell} \equiv \sum_{i \neq j} q_{im}^{\ell}$, and $q_{(-j)m}^{d} \equiv \sum_{i \neq j} q_{im}^{d}$. These show that the presence of transaction costs generates a link between deposits and loans at the bank level. The within-bank transaction cost θ_w generates a positive relationship between local deposits and loans. Similarly, the transaction cost in the interbank market θ_b generates a link between a bank's total deposits and loans, e.g., an increase in a bank's total deposits implies an increase in the amount of loans in every local market.

Using these optimality conditions, and the definition of the frictionless equilibrium quantities $q_m^{\ell*}$ and q_m^{d*}, we obtain the following expressions for equilibrium quantities. For every bank j,

$$q_{jm}^{\ell} = q_m^{\ell*} - \frac{1}{N_m + 1 + 2\theta_w}\left[\theta_w\left(q_m^{\ell*} - q_m^{d*}\right) + \theta_b\left(Q_j^\ell - Q_j^d\right)\right]$$

$$q_{jm}^{d} = q_m^{d*} + \frac{1}{N_m + 1 + 2\theta_w}\left[\theta_w\left(q_m^{\ell*} - q_m^{d*}\right) + \theta_b\left(Q_j^\ell - Q_j^d\right)\right]$$

(4)

which yields the following expression for the equilibrium level of net borrowing:

$$q_{jm}^{\ell} - q_{jm}^{d} = \frac{N_m + 1}{N_m + 1 + 2\theta_w}\left(q_m^{\ell*} - q_m^{d*}\right) - \frac{2\theta_b}{N_m + 1 + 2\theta_w}\left(Q_j^\ell - Q_j^d\right)$$

(5)

For notational simplicity, these equations use the endogenous variable $Q_j^\ell - Q_j^d$ instead of its equilibrium value in terms of exogenous variables. This equilibrium value is:

$$Q_j^\ell - Q_j^d = \frac{N + 1}{N + 1 + 2[\theta_w + \theta_b M]}\left(Q^{\ell*} - Q^{d*}\right)$$

(6)

where $N = M^{-1}\sum_{m=1}^{M} N_m$, and $Q^{\ell*}$ and Q^{d*} are the national amounts of loans and deposits per-bank, respectively, in the economy without frictions.

2.3 Predictions

Suppose that in market m the social value of loans is greater than the social value of deposits such that $q_m^{\ell*} > q_m^{d*}$. Suppose further that $Q_j^{\ell} - Q_j^d = 0$. Then, equation (5) establishes that, in the equilibrium with frictions, we have that $q_{jm}^{\ell} - q_{jm}^d = [(N_m+1)/(N_m+1+2\theta_w)](q_m^{\ell*} - q_m^{d*}) < (q_m^{\ell*} - q_m^{d*})$. That is, this market cannot borrow as much as it would like if there were no frictions. Similarly, if the local market is a net lender, $q_m^{\ell*} < q_m^{d*}$, and $Q_j^{\ell} - Q_j^d = 0$, we have that $(q_{jm}^{\ell} - q_{jm}^d) > (q_m^{\ell*} - q_m^{d*})$ such that this market cannot lend as much as it would like in the absence of frictions.

This depends on the market structure in the local market. When the number of banks increases such that $(N_m + 1)/(N_m + 1 + 2\theta_w)$ goes to one, the within-bank transaction cost has no effect. In contrast, in a monopoly market we have that $q_{jm}^{\ell} - q_{jm}^d = (q_m^{\ell*} - q_m^{d*})/(1+\theta_w)$, which can be much smaller than net borrowing without frictions. Equation (4) shows that this occurs by reducing the local amount of loans (i.e., $q_{jm}^{\ell} < q_m^{\ell*}$) and increasing the local amount of deposits (i.e., $q_{jm}^d > q_m^{d*}$).

Now, consider the effects of θ_b. Suppose the market is a net borrower, $q_m^{\ell*} > q_m^{d*}$, and the economy as a whole is also in a borrowing position, $Q_j^{\ell} - Q_j^d > 0$. In this case, the term $-[2\theta_b/(N_m + 1 + 2\theta_w)] \left(Q_j^{\ell} - Q_j^d \right)$ is negative such that the friction in the interbank market contributes to further limit the amount of borrowing in market m. This effect could be strong enough to change the sign of $q_{jm}^{\ell} - q_{jm}^d$ from positive to negative such that market m could become a net lender. As in the case of the within-bank friction, the effect of the interbank friction depends on local market structure. With sufficient competition, the interbank friction has no effect.

Optimal interbank rate. So far, we have considered that the interest rate in the interbank market, r_0, is exogenously given. Now, we consider the question of what is the value of r_0 that maximizes total welfare in this economy. It is possible to show that the optimal rate is the one that eliminates the negative welfare effect from the friction in the interbank market. This is achieved when $Q_j^{\ell} - Q_j^d = 0$, or equivalently when $Q^{\ell*} - Q^{d*} = 0$. That is, the optimal rate, r_0^*, is such that:

$$Q^{\ell*} = \sum_{m=1}^{M} \frac{a_m^{\ell} - c_m^{\ell} - r_0^*}{N_m + 1} = \sum_{m=1}^{M} \frac{a_m^d - c_m^d + r_0^*}{N_m + 1} = Q^{d*}. \tag{7}$$

This implies,

$$r_0^* = \frac{\sum_{m=1}^{M} \dfrac{\left(a_m^{\ell} - c_m^{\ell} \right) - \left(a_m^d - c_m^d \right)}{N_m + 1}}{\sum_{m=1}^{M} \dfrac{2}{N_m + 1}}.$$

Note that we have that $Q^{\ell} = Q^{\ell*}$ and $Q^d = Q^{d*}$, such that θ_w and θ_b have no effect on aggregate deposits and loans. However, θ_w still has an effect on the allocation of credit across markets and on welfare. Welfare monotonically declines with θ_w and reaches its maximum when $\theta_w = 0$.

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2.4 Diffusion index

This framework can be used to understand the extent to which funding flows across markets and the role that frictions play in affecting this flow. To study these questions we develop a measure of diffusion of funding. We borrow from the literature on racial geographic segregation to construct a measure of the transfer of funds across markets. We label this measure the *diffusion index*:

$$DI \equiv \frac{1}{2} \sum_{m=1}^{M} \left| \frac{q_m^\ell}{Q^\ell} - \frac{q_m^d}{Q^d} \right| \tag{8}$$

To characterize the determinants of the DI, it is convenient to consider the case where there the interest rate in the interbank market is chosen optimally such that at the national level $Q^\ell = Q^d = Q^*$. Then, the model implies that the DI is equal to:

$$
\begin{aligned}
DI &\equiv \frac{1}{2} \sum_{m=1}^{M} \left| \frac{q_m^\ell - q_m^d}{Q^*} \right| \\
&= \frac{1}{2} \sum_{m=1}^{M} \left| \left(\frac{N_m + 1}{N_m + 1 + 2\theta_w} \right) \left(\frac{q_m^{\ell*} - q_m^{d*}}{Q^*} \right) \right| \\
&= \frac{1}{2} \sum_{m=1}^{M} \psi_m \, |\Delta_m^*|
\end{aligned}
\tag{9}
$$

ψ_m is an index that captures both the inefficiency due to θ_w, and local market competition. It increases with competition and declines with the friction. Δ_m^* represents the imbalance between loans and deposits in market m.

It is clear from equation (9) that the DI declines monotonically with θ_w. An increase in the within-bank transaction cost implies a reduction in the diffusion of bank funds as measured by the DI. To discuss the different determinants of the DI, we can use the following representation:

$$DI = \frac{1}{2} \left[\overline{\psi} \, \sigma_\Delta + \sigma_{\psi,\Delta} \right]$$

where $\overline{\psi} \equiv M^{-1} \sum_{m=1}^{M} \psi_m$; $\sigma_\Delta \equiv \sum_{m=1}^{M} |\Delta_m^*|$; and $\sigma_{\psi,\Delta} \equiv \sum_{m=1}^{M} (\psi_m - \overline{\psi}) \, |\Delta_m^*|$. There are four forces that determine the diffusion index (DI).

(i) The level of (exogenous) endowed imbalances between deposits and loans, as measured by σ_Δ. In the extreme case where these imbalances are zero (i.e., $\Delta_m^* = 0$ for every market m), we have that the DI is zero. The DI increases monotonically with σ_Δ.

(ii) The within-bank transaction cost parameter θ_w, that has a negative impact on DI through $\overline{\psi}$.

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(iii) The average degree of competition in the M markets, that has a positive impact on DI through $\overline{\psi}$. Competition has a positive impact on the DI.

(iv) The term $\sigma_{\psi,\Delta}$ that represents the covariance between local market competition (as measured by ψ_m) and the exogenous local imbalance $|\Delta_m^*|$. For instance, if larger markets attract more banks and can be endowed with larger imbalances, then $\sigma_{\psi,\Delta} > 0$ and this correlation contributes positively to the DI.

In what follows, we will use the Diffusion Index to test empirically the extent to which frictions prevent funding to flow geographically.

3 Data and descriptive evidence

3.1 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 collected on 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, address, 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.[8]

Under the HMDA, most mortgage lending institutions are required to disclose information on the mortgage loans that they originate or purchase in a given year.[9] 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.

The type of institutions reporting to HMDA include both depository institutions and non-depository institutions, mainly Independent Mortgage Companies (IMCs).[10] By definition, only

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[8]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.

[9]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 provides information on the majority of residential mortgage lending activities.

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

the former, including banks and thrifts, can be matched with the SOD data.[11] Other than 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 Census Bureau. The US Census Bureau provides various data products through which we obtain detailed county level characteristics to estimate our model. Population counts by age, gender, and ethnic group are obtained from 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, 2016), and county-level bankruptcy data from the U.S. Bankruptcy Courts.[12] 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 (OTS)'s Thrift Financial Report (TFR) for saving associations.

There are three features of our data and empirical approach that deserve specific discussion.

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[11]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.

[12]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.

First, we have data on mortgage loans at the bank-county-year level but we do not have data on other forms of bank credit. Ideally, we would like to use information on other types of bank loans, but, to our knowledge, such data are not publicly available at the bank-county-year level. 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 (2016) 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. Therefore, our focus on deposits and mortgages, though motivated by data availability, captures a very substantial fraction of total bank liabilities and assets, respectively. Furthermore, other sorts of loans may be taken out at one location, but used to finance projects elsewhere. This would make studying the flow of funding and access to credit difficult. In contrast, mortgages are much more local.

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 focus is that consumers can choose in every period where to put their entire stock of deposits and where to get new loans, rather than either the stock of both deposits and loans or only new deposits and new loans. 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 contain 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 necessary to comment on the fact 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 Ashcraft, 2005; Calomiris and Mason, 2003; Huang, 2008; Gowrisankaran and Krainer, 2011; and Uetake and Wanatabe, 2012).

3.2 Summary statistics

We concentrate on the period 1998-2010. Our matched sample includes 7821 depository banks and $3,655$ non-depository banks in 3146 counties.[13] For the rest of the paper, we use the term *shadow bank* to refer the non-depository banks in our dataset. 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 shadow banks.

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[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 shadow 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 3146 counties in our analysis.

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
Shadow 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 ≤ 19 (in %)	27.4	3.4	22.2	27.3	33.2
Share population ≥ 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

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 2535 for deposit markets (i.e., equivalent to 4 symmetric banks per market) and 633 for loan markets (i.e., equivalent to a market with 16 symmetric banks). A possible explanation of this evidence 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 1 to 4 present time series of some aggregate magnitudes from our working sample, i.e., deposits, mortgages, loans, banks, and branches) over our sample period. Figure 1 presents the evolution of the stock of deposits and the flow of new mortgage loans aggregated over all banks and counties with a yearly frequency. Both time series follow a similar pattern, with strong growth in the early 2000s followed by a decline of new mortgages and a very modest increase of deposits in the last years of the decade. Figure 2 provides evidence on the importance of 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. Figure 3 provides evidence on the share of deposits in liabilities for lenders in the HMDA dataset. The median share is around 80%.

Figures 4a and 4b 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. Note that the increase from 1998 to 2009 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 4a and 4b 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 after the crisis and then decreases slightly. In the estimation of our model, we account for competition in deposits and loans 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.

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[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.

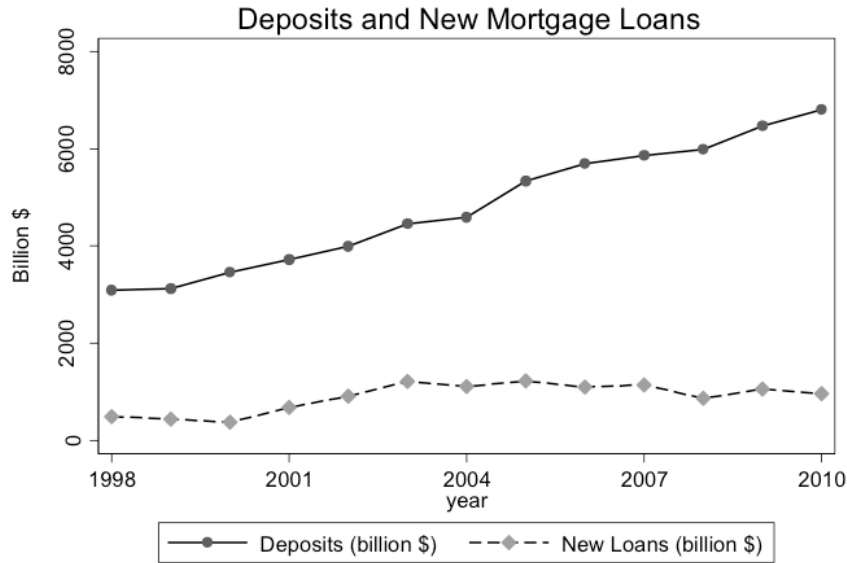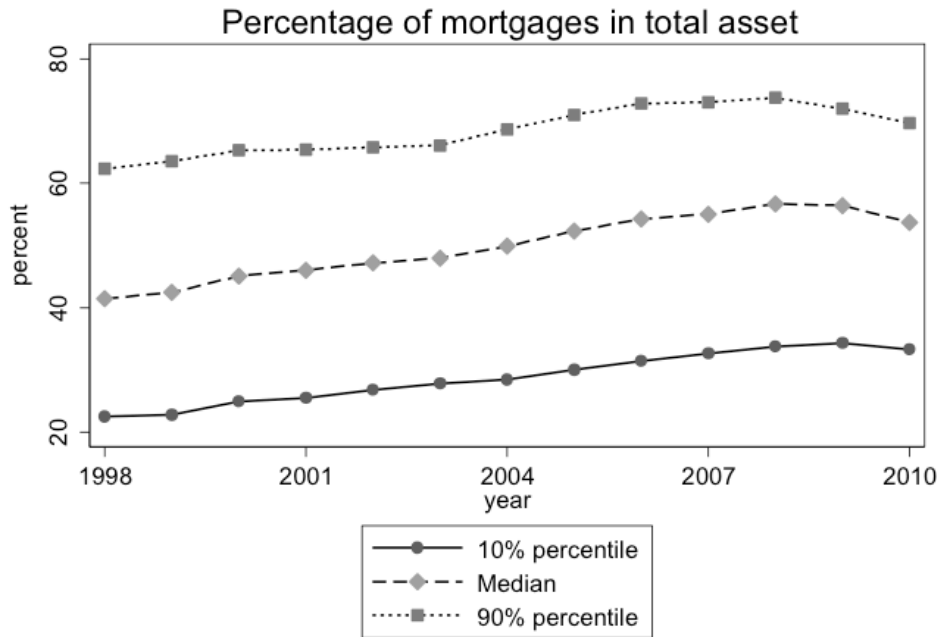Figure 1: Time Series of Stock of Deposits and Flow of New Mortgage Loans

Figure 2: Share of Mortgage Loans in Total Assets

3.3 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 techniques developed in sociology and labour economics to measure residential segregation. These capture the degree to which individuals from different social groups
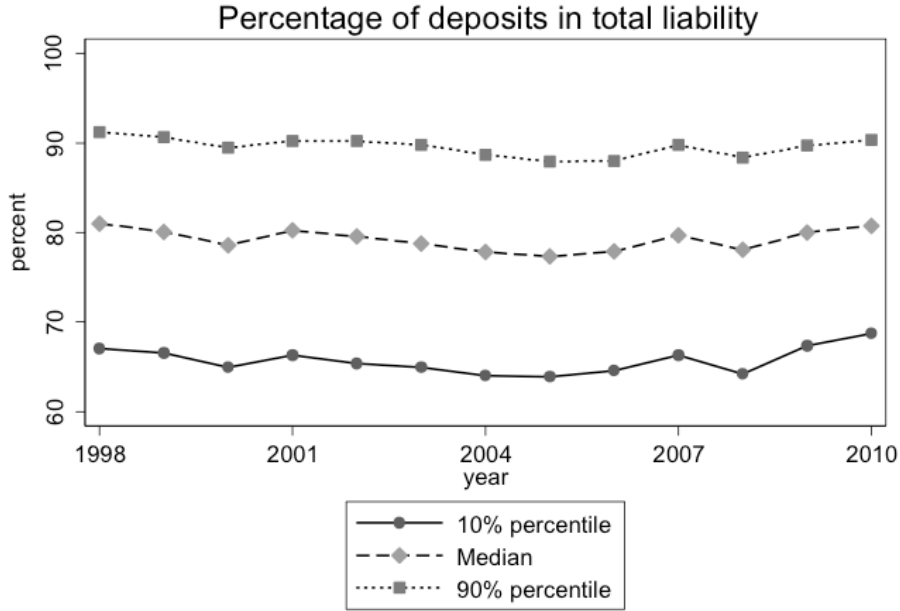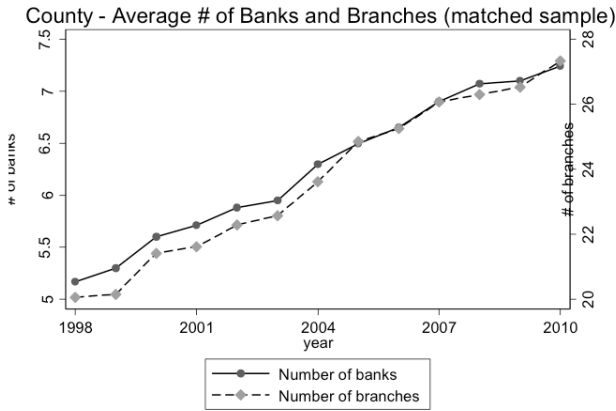
Figure 3: Share of Deposits in Liabilities

Figure 4: Number of banks and branches by county

(a) SOD-HMDA Matched Sample

(b) All SOD Banks
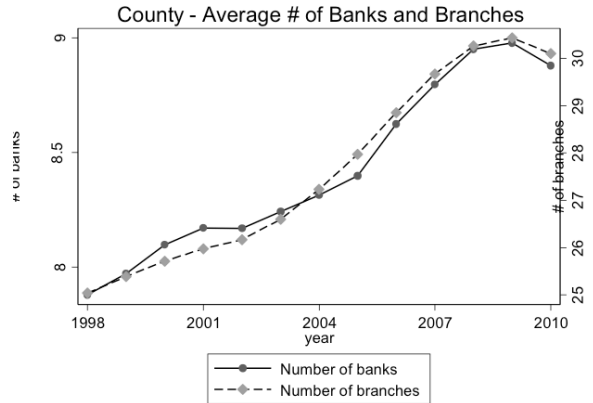
are geographically separated (Duncan and Duncan, 1955; Atkinson, 1970; White, 1983 and 1986; and Cutler et al., 1999). In our case, we are interested in segregation between the geographic distributions of deposits and loans, either for a single bank or for all the banks.

Figure 5 presents maps with the geographic distribution of counties' positions as net borrowers or net lenders. We present these maps for three different years in our sample: 1999, 2004, and 2009. We first describe the construction of the statistics in these figures. 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 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 5 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.

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.

Figure 5: Distribution of borrower/lender counties

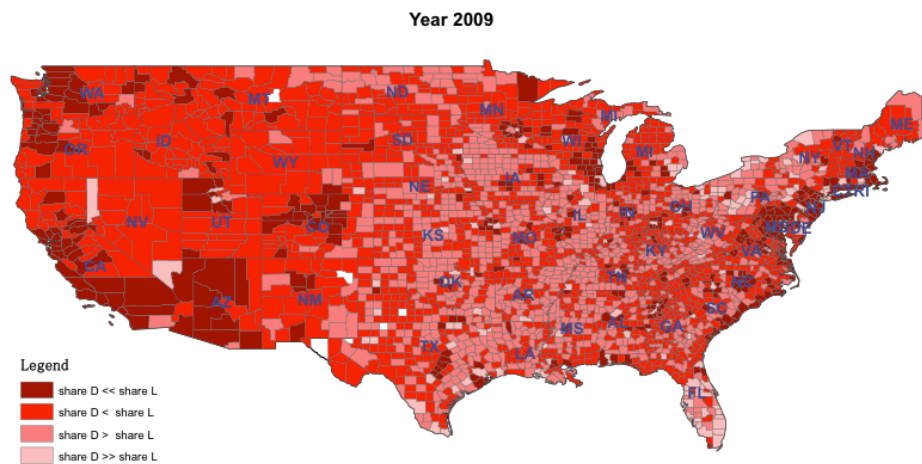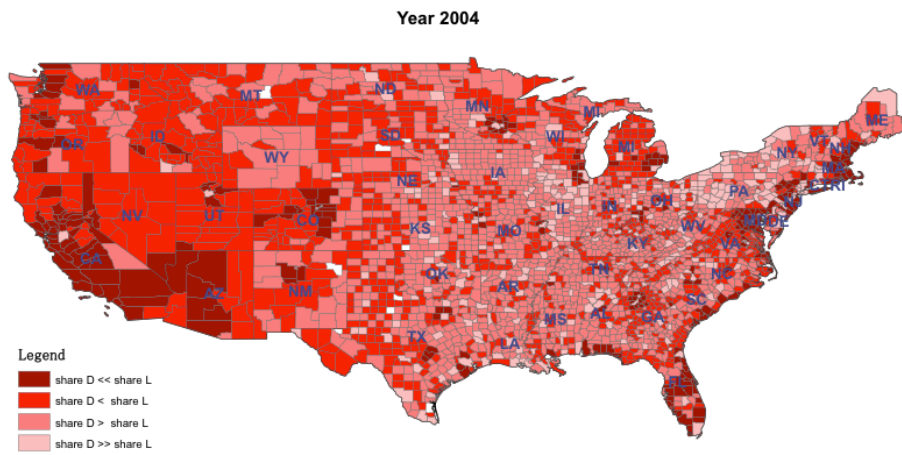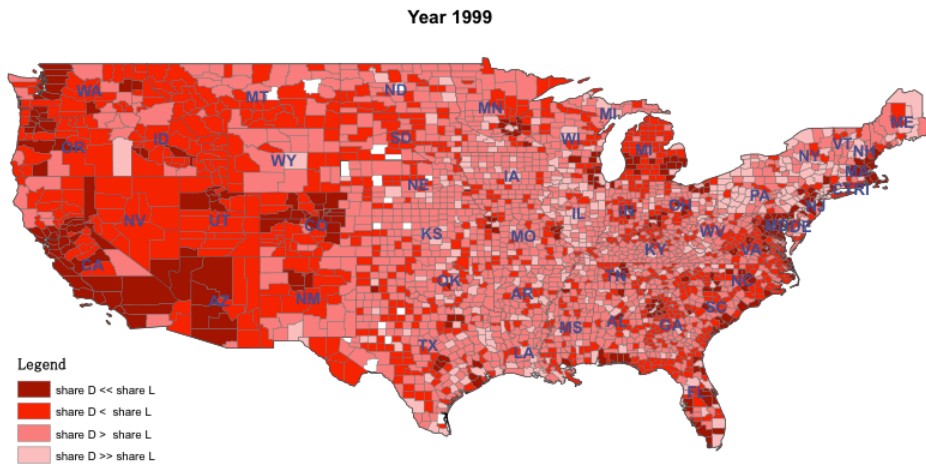**Year 1999**

Year 2004

Year 2009

Table 2 provides further insight into the changes over time. While many counties maintain their status as weak/strong lender/borrowers, there is significant turnover. This is especially true for counties that were weak/strong lenders in 1999. A large number of counties that were weak lenders in 1999, became weak borrowers in 2009. Similarly, many counties that were strong lenders in 1999, became weak lenders.

Table 2
Transition matrix for county borrowing /lending category from 1999 to 2009

			2009			
			share D $<<$ share L	share D $<$ share L	share D $>$ share L	share D $>>$ share L
			413	1595	943	162
	share D $<<$ share L	288	86.2%	6.6%	1.4%	5.5%
1999	share D $<$ share L	1048	11.2%	84.3%	3.0%	0.9%
	share D $>$ share L	1378	1.6%	45.8%	52.0%	0.6%
	share D $>>$ share L	399	6.0%	14.3%	47.6%	32.1%

Figure 6 presents the empirical distribution of *segregation indexes* calculated at the bank-year level. Borrowing from the literature on racial geographic segregation,[15] we calculate the *segregation index*: $(1/2)\sum_m |q^d_{jmt}/Q^d_{jt} - q^\ell_{jmt}/Q^\ell_{jt}|$, where q^d_{jmt} and q^ℓ_{jmt} represent the amount of deposits and loans, respectively, of bank j in county m and year t, 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 bank's transfer of funds between geographic locations (counties) or, alternatively, a measure of the bank's home bias.[16] For instance, a segregation 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, a segregation index equal one means that the bank gets all its deposits in markets where does not provide loans, and sells loans only in markets where does not have deposits, which is an extreme case of geographic diffusion of loans.

From Figure 6 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

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[15]This type of index was first proposed by Jahn, Schmid, and Schrag (1947).

[16]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 segregation 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.

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).[17] For these banks the segregation scores are 0.45 in 1999, 0.43 in 2004 and 0.52.

Figure 6: Segregation Indexes between Deposit and Loan Distributions–Bank level
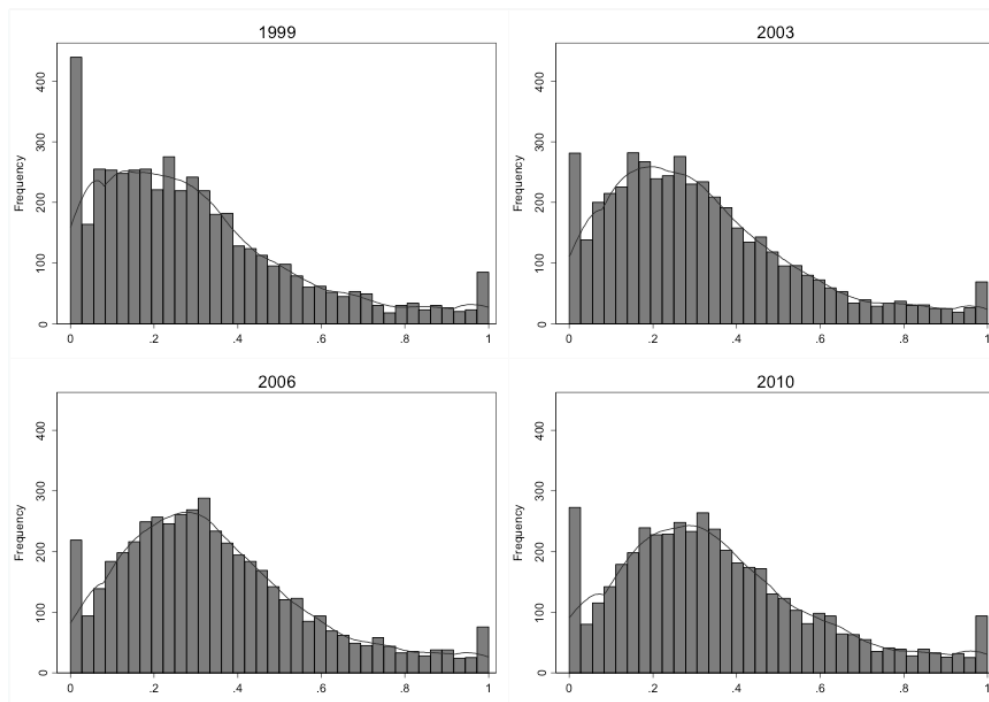
This increase over time is also noticeable in Figure 7 which presents the time series of a national level segregation index calculated using county level observations. This segregation index is defined as:

$$SI_t = \frac{1}{2} \sum_{m=1}^{M} \left| \frac{Q_{mt}^d}{Q_t^d} - \frac{Q_{mt}^\ell}{Q_t^\ell} \right| \tag{10}$$

where $\frac{Q_{mt}^d}{Q_t^d}$ and $\frac{Q_{mt}^\ell}{Q_t^\ell}$ are the shares of county m in the aggregate national amounts of deposits and new mortgage loans, respectively. This index measures the transfer of funds between geographic locations. Figure 7a presents the national index for our matched sample. It exhibits a cyclical trend, although the overall level of variation is quite small, i.e., between 0.28 and 0,32. Figure 7b uses the full sample that includes also shadow banks. It displays the same general trend confirming

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[17]Specifically, since we are interested in calculating the segregation 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.

that shadow banks are not lending to different markets than traditional banks.

Figure 7: Time Series of the National Segregation Index

(a) SOD-HMDA Matched Sample

(b) All SOD Banks
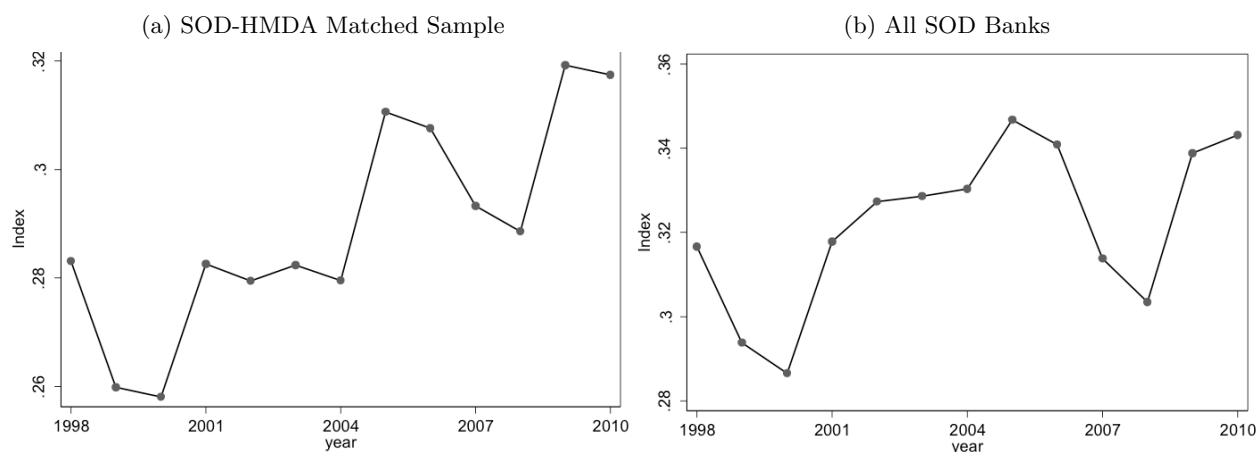
3.4 Local market power and the effect of total deposits and local loans

In this subsection we provide descriptive evidence on the extent to which local market power impacts the flow of deposits across markets. Specifically, we are interested in measuring the effect that the structures of loan and deposit markets have on the elasticity of local mortgage loans or deposits with respect to banks' total amount of deposits. Given the relatively low level of concentration in local mortgage markets, one might argue that market power in loan markets is quite modest in most counties and it should not have an important impact on the geographic diffusion of credit. However, there is substantial heterogeneity across counties in the degree of concentration of their mortgage markets. Also, in addition to a direct effect on local deposit markets, market power in deposit markets could have a spillover effect on local loan markets through economies of scope.

The first and third quartiles in the distribution of the number of banks in mortgage markets are 11 and 21, respectively. For the distribution of the HHI these quartiles are 416 and 1016. Therefore, some banks face substantial heterogeneity in the degree of market power that they enjoy in the different counties where they operate. Given this heterogeneity in local market power, a bank is more willing to transfer funds to those counties where competition is more intense and limit the amount of credit in more concentrated counties.

Table 3 presents descriptive, reduced-form, evidence on the role that local market power plays in a bank's allocation of funds over the different counties where it operates. We present fixed-effects regressions where the dependent variable is the logarithm of the value of a bank's mortgage loans in a county ($\ln q_{jmt}^{\ell}$), and the key explanatory variables are the logarithm of the bank's total amount

of deposits ($\ln Q_{jt}^d$), and the interactions of this variable with the number of banks in the county's loan market and in the county's deposit market compared to the national average, $[N_{mt}^\ell - \overline{N}^\ell] \ln Q_{jt}^d$ and $[N_{mt}^d - \overline{N}^d] \ln Q_{jt}^d$, respectively. That is,

$$\ln q_{jmt}^\ell = \beta_1 \ln Q_{jt}^d + \beta_2 [N_{mt}^\ell - \overline{N}^\ell] \ln Q_{jt}^d + \beta_3 [N_{mt}^d - \overline{N}^d] \ln Q_{jt}^d + \mathbf{z}_{mt}' \gamma + \alpha_{jm} + \delta_t + \varepsilon_{jmt} \quad (11)$$

$\overline{N}^\ell$ and $\overline{N}^d$ are the sample means of the variables N_{mt}^ℓ and N_{mt}^d, respectively, such that the parameter β_1 represents the elasticity between local loans and global deposits evaluated at the sample mean of the local market structure, and the parameters β_2 and β_3 capture deviations with respect to this average elasticity. The vector of control variables $\mathbf{z}_{mt}$ includes the logarithm of income per capita, log population, log housing price index, log bankruptcy filings, share of population younger than 20 years old, share of population older than fifty years old, and the number of banks in the local loans and deposits markets, N_{mt}^ℓ and N_{mt}^d. The terms α_{jm} and δ_t represent bank-county fixed effects and time (year) fixed effects, respectively.

The estimation results in Table 3 show that local market structure in the loans market has a significant effect on the elasticity of local mortgage loans with respect the bank's total amount of deposits. Evaluated at the sample mean N_{mt}^ℓ (i.e., 45 banks) this elasticity is equal to 0.16, but it increases significantly with the number of banks, by 0.0015 per bank such that it is equal to 0.10 in a market with 6 banks (i.e., at the 5% percentile), and 0.28 in a market with 125 banks (i.e., at the 95% percentile). The number of banks in the local deposits market has also a positive effect on this elasticity, though the effect has a smaller magnitude. In the equation for local bank deposits, we find that the elasticity increases significantly with the number of banks in the deposits market but it does not depend on the number of banks in the local mortgage market.

Table 3
Local market power and the elasticity of local loans (and local deposits)
with respect to global deposits[1]

Variable	log bank local loans	log bank local deposits
log bank total deposits ($\ln Q_{jt}^d$)	0.1626*** (0.0035)	0.4939*** (0.0132)
$[N_{mt}^\ell - \overline{N}^\ell] \ln Q_{jt}^d$	0.0015*** (0.0001)	0.0001 (0.0001)
$[N_{mt}^d - \overline{N}^d] \ln Q_{jt}^d$	0.0011** (0.0003)	0.0029*** (0.0002)
Control variables[2]		
log income	0.1052* (0.0416)	0.3057*** (0.0472)
log population	0.8768*** (0.0514)	0.9928*** (0.0700)
share young	-5.5584*** (0.5163)	4.2324*** (0.6957)
share old	-1.1805** (0.3384)	2.6360*** (0.4559)
log housing price index	0.9087*** (0.0235)	0.2526*** (0.0252)
log bankruptcy filings	-0.0596*** (0.0064)	0.0124* (0.0051)
Bank × County Fixed Effects	YES	YES
Time Dummies	YES	YES
Control Variables[2]	YES	YES
Number of observations	1,502,767	204,174
R-square within	0.1143	0.3157
R-square overall	0.1824	0.2167

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
Note 2: Set of control variables: log income per capita, log population, log housing price index,
log bankruptcy filings, share of population younger than 20 years old, share of population
older than 50 years old, and the number of banks in the local loans and deposits markets.

4 Empirical Model

Consider an economy with M geographic markets (counties), indexed by $m \in \mathcal{M} = \{1, 2, ..., M\}$, and J banks, indexed by $j \in \{1, 2, ..., J\}$. Let $\mathcal{M}_j^d$ represent the set of markets where bank j has branches and sells deposits. Similarly, $\mathcal{M}_j^\ell$ represents the set of markets where bank j sells loans. This set of markets $\mathcal{M}_j^\ell$ 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, $\mathcal{M}_j^\ell$ includes the set $\mathcal{M}_j^d$ but it can be larger, i.e., $\mathcal{M}_j^d \subseteq \mathcal{M}_j^\ell$.

We take networks $\{\mathcal{M}_j^d\}_{j=1}^J$ and $\{\mathcal{M}_j^\ell\}_{j=1}^J$ as given. 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. We consider the networks to be pre-determined 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.

Each local market is populated by two groups of consumers: *savers* who demand deposit products, and *investors* who demand loan products. 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.

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, and minus the costs (or returns) from the bank's activity in interbank wholesale markets:

$$\Pi_j = \sum_{m=1}^M p_{jm}^\ell \, q_{jm}^\ell + p_{jm}^d \, q_{jm}^d - C_{jm}\left(q_{jm}^\ell, q_{jm}^d\right) - (r_0 + c_{j0})\, B_j \tag{12}$$

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

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

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 should pay 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 r_0 is determined by the Federal Reserve, and it 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. A bank's resources constraint implies that,[19] $B_j = Q_j^\ell - Q_j^d$, 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. 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.

In our model, the balance sheet or resource constraints of every bank, and of the banking system as a whole, are always satisfied. Given the price 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, as mentioned above, $B_j = Q_j^\ell - Q_j^d$. This condition implies that the bank's resource constraint is always satisfied.[20] Given the net positions of all the banks in the interbank market, and the position of the Federal Reserve, as represented by B_0, there is an interest rate r_0 that clears the interbank market such that the equilibrium condition $\sum_{j=1}^J B_j + B_0 = 0$ is satisfied. Our model does not explicitly incorporate the equilibrium in the interbank market, though it generates endogenously the position of every bank in this market, B_j.

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.

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[19]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.

[20]Note that, for simplicity, our model does not incorporate capital requirements or reserve ratios that would impose inequality restrictions on B_j.

4.1 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. 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):

$$u_{jm}^d = \mathbf{x}_{jm}^d \ \beta^d - \alpha^d \ p_{jm}^d + \xi_{jm}^d + \varepsilon_{jm}^d \tag{13}$$

$\mathbf{x}_{jm}^d$ 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 $\mathbf{x}_{jm}^d$. These marginal utilities may vary across markets according to observable and unobservable (to the researcher) market characteristics, e.g., per capita income, age distribution, etc. Variable p_{jm}^d is the price of deposit services (i.e., consumer fees minus the deposit interest rate), and α^d is the marginal utility of income. The term ξ_{jm}^d represents other characteristics of bank j in market m that are observable and valuable to savers but unobservable for us as researchers. Variables ε_{jm}^d 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 $s_{jm}^d \equiv q_{jm}^d / H_m^d$ be the market share of bank j in the market for deposits at location m. The model implies that:

$$s_{jm}^d = \frac{1\left\{m \in \mathcal{M}_j^d\right\} \ \exp\left\{\mathbf{x}_{jm}^d \ \beta^d - \alpha^d \ p_{jm}^d + \xi_{jm}^d\right\}}{1 + \sum_{k=1}^{J} 1\left\{m \in \mathcal{M}_k^d\right\} \ \exp\left\{\mathbf{x}_{km}^d \ \beta^d - \alpha^d \ p_{km}^d + \xi_{km}^d\right\}} \tag{14}$$

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

The vector of product characteristics $\mathbf{x}_{jm}^d$ 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_{jm}^ℓ); and (iii) the bank's total amount of deposits (Q_j^d). The number of branches captures the effects of consumer transportation costs as well as consumer awareness about the bank's presence. The share in the local market for loans captures economies of scope at the consumer level

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[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.

from having deposits and loans at the same bank, i.e., one-stop banking.[22] The bank's total deposits capture consumers' concerns for the probability of default or bank-run. Therefore, we have that,

$$\mathbf{x}_{jm}^d \beta^d = \mathbf{z}_m \ \beta_0^d + \beta_n^d \ h(n_{jm}) + \beta_\ell^d \ s_{jm}^\ell + \beta_Q^d \ \ln Q_j^d \tag{15}$$

$\mathbf{z}_m$ 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 $s_{jm}^d = d_{jm}(p_{jm}^d, s_{jm}^\ell, Q_j^d)$ to represent the demand for deposits, where, for notational convenience, we include explicitly as arguments the endogenous variables $(p_{jm}^d, s_{jm}^\ell, Q_j^d)$.

(b) Demand for loan products. Each local market is also populated by investors / borrowers. Let H_m^ℓ be the number of new borrowers in market m. Each (new) borrower is endowed with an investment project that requires 1 unit of loans. 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 $\mathcal{M}_j^d \subseteq \mathcal{M}_j^\ell$). 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:

$$u_{jm}^\ell = \mathbf{x}_{jm}^\ell \ \beta^\ell - \alpha^\ell \ p_{jm}^\ell + \xi_{jm}^\ell + \varepsilon_{jm}^\ell \tag{16}$$

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

$$s_{jm}^\ell = \frac{1\left\{m \in \mathcal{M}_j^\ell\right\} \ \exp\left\{\mathbf{x}_{jm}^\ell \ \beta^\ell - \alpha^\ell \ p_{jm}^\ell + \xi_{jm}^\ell\right\}}{1 + \sum_{k=1}^J 1\left\{m \in \mathcal{M}_k^\ell\right\} \ \exp\left\{\mathbf{x}_{km}^\ell \ \beta^\ell - \alpha^\ell \ p_{km}^\ell + \xi_{km}^\ell\right\}} \tag{17}$$

As was the case for deposits, the vector of product characteristics $\mathbf{x}_{jm}^\ell$ includes: (i) the number of branches (n_{jm}); (ii) the bank's share of the local market for deposits (s_{jm}^d); and (iii) the bank's total amount of deposits in all the markets (Q_j^d). As explained above for the demand for deposits,

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[22]Ideally, we would 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 Gentzkow (2007) and Allen, Clark, and Houde (2017). Unfortunately, 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.

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 either because it is related to the bank's risk of liquidity shortage and default, or because there is some *renewal risk* that the bank initially contracted with goes under and the new owner of the loan does not want to renew. Consumers value a bank's total amount of deposits because it is related to the bank's risk of liquidity shortage and default. Thus, we have that

$$\mathbf{x}_{jm}^{\ell}\beta_m^{\ell} = \mathbf{z}_m\ \beta_0^{\ell} + \beta_n^{\ell}\ h(n_{jm}) + \beta_d^{\ell}\ s_{jm}^d + \beta_Q^{\ell}\ \ln Q_j^d. \tag{18}$$

We use the function $s_{jm}^{\ell} = \ell_{jm}(p_{jm}^{\ell}, s_{jm}^d, Q_j^d)$ to represent the demand for loans.

(c) Demand system for deposits and loans. The demand system can be represented by the equations $s_{jm}^{\ell} = \ell_{jm}(p_{jm}^{\ell}, s_{jm}^d, Q_j^d)$ and $s_{jm}^d = d_{jm}(p_{jm}^d, s_{jm}^{\ell}, Q_j^d)$. 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 $\{s_{jm}^{\ell}, s_{jm}^d\}$ implies the *reduced form demand system*:

$$s_{jm}^d = f_{jm}^d\left(\mathbf{p}_j^d, \mathbf{p}_j^{\ell}\right) \quad \text{and} \quad s_{jm}^{\ell} = f_{jm}^{\ell}\left(\mathbf{p}_j^d, \mathbf{p}_j^{\ell}\right) \tag{19}$$

where $\mathbf{p}_j^d$ and $\mathbf{p}_j^{\ell}$ 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, $\partial f_{jm}^d/\partial p_{jm}^{\ell}$ or $\partial f_{jm}^{\ell}/\partial p_{jm}^d$, incorporate *local and global multiplier effects*. For instance, 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:

$$
\begin{aligned}
\frac{\partial f_{jm}^{\ell}}{\partial p_{jm}^{\ell}} &= \frac{\partial \ell_{jm}}{\partial p_{jm}^{\ell}} + \frac{\partial \ell_{jm}}{\partial s_{jm}^d}\frac{\partial f_{jm}^d}{\partial p_{jm}^{\ell}} + \frac{\partial \ell_{jm}}{\partial Q_j^d}\left[\sum_{m'\in\mathcal{M}_j^d}\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}}\right] \\[2ex]
\frac{\partial f_{jm}^d}{\partial p_{jm}^{\ell}} &= \frac{\partial d_{jm}}{\partial s_{jm}^{\ell}}\frac{\partial f_{jm}^{\ell}}{\partial p_{jm}^{\ell}} + \frac{\partial d_{jm}}{\partial Q_j^d}\left[\sum_{m'\in\mathcal{M}_j^d}\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}}\right] \\[2ex]
\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}} &= \frac{\partial d_{jm'}}{\partial s_{jm'}^{\ell}}\frac{\partial f_{jm'}^{\ell}}{\partial p_{jm}^{\ell}} + \frac{\partial d_{jm'}}{\partial Q_j^d}\left[\sum_{m'\in\mathcal{M}_j^d}\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}}\right] \quad \text{for } m'\neq m \\[2ex]
\frac{\partial f_{jm'}^{\ell}}{\partial p_{jm}^{\ell}} &= \frac{\partial \ell_{jm'}}{\partial s_{jm'}^d}\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}} + \frac{\partial \ell_{jm'}}{\partial Q_j^d}\left[\sum_{m'\in\mathcal{M}_j^d}\frac{\partial f_{jm'}^d}{\partial p_{jm}^{\ell}}\right] \quad \text{for } m'\neq m
\end{aligned}
\tag{20}
$$

This is a system of linear equations in the vector of partial derivatives $\{\partial f_{jm'}^{\ell}/\partial p_{jm}^{\ell}; \partial f_{jm'}^{d}/\partial p_{jm}^{\ell}:$ 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. More formally, let $\partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{\ell}$ be the $|\mathcal{M}_j^{\ell}| \times 1$ vector of partial derivatives $\{\partial f_{jm'}^{\ell}/\partial p_{jm}^{\ell}:$ $m' \in \mathcal{M}_j^{\ell}\}$, and similarly, let $\partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{d}$ be the $|\mathcal{M}_j^d| \times 1$ vector $\{\partial f_{jm'}^{d}/\partial p_{jm}^{\ell} : m' \in \mathcal{M}_j^{\ell}\}$. The system of equations (20) implies the following *solution* for $[\partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{\ell}, \partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{d}]$ in terms of derivatives of the structural demand functions:

$$
\begin{bmatrix} \partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{\ell} \\ \partial \mathbf{f}_{j,(p_{jm}^{\ell})}^{d} \end{bmatrix} = \left[\mathbf{I} - \begin{pmatrix} \mathbf{0}_{|\mathcal{M}_j^{\ell}| \times |\mathcal{M}_j^{\ell}|} & ; & \mathbf{A}_{j,(p_{jm}^{\ell})} \\ \mathbf{B}_{j,(p_{jm}^{\ell})} & & \mathbf{C}_{j,(p_{jm}^{\ell})} \end{pmatrix} \right]^{-1} \begin{bmatrix} \mathbf{i}_{|\mathcal{M}_j^{\ell}|}^{(m)} \partial \ell_{jm}/\partial p_{jm}^{\ell} \\ \mathbf{0}_{|\mathcal{M}_j^d|} \end{bmatrix} \tag{21}
$$

where $\mathbf{I}$ is the identify matrix; $\mathbf{0}$ is a matrix of zeros; $\mathbf{i}_{|\mathcal{M}_j^{\ell}|}^{(m)}$ is a vector with 1 at the m-th element and zeroes elsewhere; and $\mathbf{A}_{j,(p_{jm}^{\ell})}$, $\mathbf{B}_{j,(p_{jm}^{\ell})}$, and $\mathbf{C}_{j,(p_{jm}^{\ell})}$ are matrices with the following definitions:

$$
\begin{aligned}
\mathbf{A}_{j,(p_{jm}^{\ell})} &\equiv diag\left\{\partial \ell_{j,s^d}\right\} + diag\left\{\partial \ell_{j,Q^d}\right\} \mathbf{1}_{|\mathcal{M}_j^{\ell}| \times |\mathcal{M}_j^d|} \\
\mathbf{B}_{j,(p_{jm}^{\ell})} &\equiv diag\left\{\partial \mathbf{d}_{j,s^{\ell}}\right\} \\
\mathbf{C}_{j,(p_{jm}^{\ell})} &\equiv diag\left\{\partial \mathbf{d}_{j,Q^d}\right\} \mathbf{1}_{|\mathcal{M}_j^d| \times |\mathcal{M}_j^d|}
\end{aligned} \tag{22}
$$

$diag\{\mathbf{v}\}$ is a diagonal matrix with vector $\mathbf{v}$ in the diagonal; $\mathbf{1}$ is a matrix of ones; $\partial \ell_{j,s^d}$ is the $|\mathcal{M}_j^{\ell}| \times 1$ vector with elements $\partial \ell_{jm}/\partial s_{jm}^d$; $\partial \ell_{j,Q^d}$ is the $|\mathcal{M}_j^{\ell}| \times 1$ vector with elements $\partial \ell_{jm}/\partial Q_j^d$; and similarly $\partial \mathbf{d}_{j,s^{\ell}}$ and $\partial \mathbf{d}_{j,Q^d}$ are the $|\mathcal{M}_j^d| \times 1$ vectors with elements $\partial d_{jm}/\partial s_{jm}^{\ell}$ and $\partial d_{jm}/\partial Q_j^d$, respectively.

4.2 Variable cost function

We consider the following specification for the variable cost function:

$$
C_{jm}\left(q_{jm}^{\ell}, q_{jm}^d\right) = \left[\mathbf{x}_{jm}^d \gamma^d + \omega_{jm}^d\right] q_{jm}^d + \left[\mathbf{x}_{jm}^{\ell} \gamma^{\ell} + \omega_{jm}^{\ell}\right] q_{jm}^{\ell} \tag{23}
$$

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

$$
\begin{aligned}
\mathbf{x}_{jm}^d \gamma^d &= \mathbf{z}_m \gamma_0^d + \gamma_n^d h(n_{jm}) + \gamma_{\ell}^d s_{jm}^{\ell} + \gamma_Q^d \ln Q_j^d \\
\mathbf{x}_{jm}^{\ell} \gamma^{\ell} &= \mathbf{z}_m \gamma_0^{\ell} + \gamma_n^{\ell} h(n_{jm}) + \gamma_d^{\ell} s_{jm}^d + \gamma_Q^{\ell} \ln Q_j^d
\end{aligned} \tag{24}
$$

The terms $\gamma_n^d h(n_{jm})$ and $\gamma_n^{\ell} h(n_{jm})$ 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 $\gamma_\ell^d \, s_{jm}^\ell$ and $\gamma_d^\ell \, s_{jm}^d$ capture economies of scope in the management of deposits at the branch level. The component $\gamma_Q^\ell \ln Q_j^d$ captures how the marginal cost of loans declines with the bank's total volume of deposits Q_j^d.

4.3 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, $\mathbf{p}_j \equiv \{p_{jm}^d : m \in \mathcal{M}_j^d; \, p_{jm}^\ell : m \in \mathcal{M}_j^\ell\}$, 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,

$$
\underbrace{\left[q_{jm}^d + \left(p_{jm}^d - \frac{\partial C_{jm}}{\partial q_{jm}^d} \right) \frac{\partial f_{jm}^d}{\partial p_{jm}^d} \right]}_{\textit{direct effect: local deposits}} \quad + \quad \underbrace{\left(p_{jm}^\ell - \frac{\partial C_{jm}}{\partial q_{jm}^\ell} \right) \frac{\partial f_{jm}^\ell}{\partial p_{jm}^d}}_{\textit{indirect effect: local loans}}
$$

$$
+ \underbrace{\sum_{m' \neq m} \left(p_{jm'}^d - \frac{\partial C_{jm'}}{\partial q_{jm'}^d} \right) \frac{\partial f_{jm'}^d}{\partial p_{jm}^d}}_{\textit{indirect effect: deposits other counties}} \quad + \quad \underbrace{\sum_{m' \neq m} \left(p_{jm'}^\ell - \frac{\partial C_{jm'}}{\partial q_{jm'}^\ell} \right) \frac{\partial f_{jm'}^\ell}{\partial p_{jm}^d}}_{\textit{indirect effect: loans other counties}} \quad = \quad 0
$$

$$(25)$$

And 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 of the demands for loans and deposits, 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. Under the logit specification of demand, the system of marginal conditions of optimality implies the following pricing equations:

$$
p_{jm}^\ell \;=\; c_{jm}^\ell + \Delta_j^\ell + \frac{1}{\alpha^\ell (1 - s_{jm}^\ell)} - \frac{\beta_\ell^d}{\alpha^d} s_{jm}^d
$$

$$(26)$$

$$
p_{jm}^d \;=\; c_{jm}^d + \Delta_j^d + \frac{1}{\alpha^d (1 - s_{jm}^d)} - \frac{\beta_d^\ell}{\alpha^\ell} s_{jm}^\ell
$$

where Δ_j^ℓ and Δ_j^d are terms that depend on marginal costs and demand aggregated over all the markets where bank j operates.

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_{0m}^d and s_{0m}^ℓ be the market shares of the outside alternative for deposits and loans in market m. The logit model implies that $\ln(s_{jm}^d/s_{0m}^d) = \mathbf{x}_{jm}^d \beta_m^d + \alpha^d \, p_{jm}^d + \xi_{jm}^d$. Subbing the pricing equations into this expression, we obtain the following system of equilibrium equations in terms of market shares:

$$y\left(s_{jm}^d, s_{0m}^d\right) = \mathbf{x}_{jm}^d \, \beta^d - \alpha^d \left[c_{jm}^d + \Delta_j^d\right] + \frac{\alpha^d \beta_d^\ell}{\alpha^\ell} s_{jm}^\ell + \xi_{jm}^d$$

$$y\left(s_{jm}^\ell, s_{0m}^\ell\right) = \mathbf{x}_{jm}^\ell \, \beta^\ell - \alpha^\ell \left[c_{jm}^\ell + \Delta_j^\ell\right] + \frac{\alpha^\ell \beta_\ell^d}{\alpha^d} s_{jm}^d + \xi_{jm}^\ell$$

(27)

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 $c_{jm}^\ell = \mathbf{x}_{jm}^\ell \, \gamma^\ell + \omega_{jm}^\ell$ and $c_{jm}^d = \mathbf{x}_{jm}^d \, \gamma^d + \omega_{jm}^d$, we can represent the system of equilibrium equations as:

$$y\left(s_{jm}^d, s_{0m}^d\right) = \mathbf{x}_{jm}^d \, \theta^d + \eta_{jm}^d$$

$$y\left(s_{jm}^\ell, s_{0m}^\ell\right) = \mathbf{x}_{jm}^\ell \, \theta^\ell + \eta_{jm}^\ell$$

(28)

where the θ's are structural parameters that depend on both demand and marginal cost parameters. More specifically, we have that $\mathbf{x}_{jm}^d \, \theta^d \equiv \mathbf{z}_m \, \theta_0^d + \theta_n^d \, h(n_{jm}) + \theta_\ell^d \, s_{jm}^\ell + \theta_Q^d \, \ln Q_j^d$, with $\theta_0^d \equiv \beta_0^d - \alpha^d \gamma_0^d$, $\theta_n^d \equiv \beta_n^d - \alpha^d \gamma_n^d$, $\theta_Q^d \equiv \beta_Q^d - \alpha^d \gamma_Q^d$, and $\theta_\ell^d \equiv \beta_\ell^d - \alpha^d \gamma_\ell^d + \alpha^d \beta_d^\ell/\alpha^\ell$. The index $\mathbf{x}_{jm}^\ell \, \theta^\ell$ 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: $\eta_{jm}^d \equiv \xi_{jm}^d - \alpha^d \, \omega_{mt}^d - \alpha^d \Delta_j^d$ and $\eta_{jm}^\ell \equiv \xi_{jm}^\ell - \alpha^\ell \, \omega_{mt}^\ell - \alpha^\ell \Delta_j^\ell$.

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.

5   Estimation of the structural model

The system of equations of the econometric model are:

$$y_{jmt}^d = \mathbf{z}_{mt}' \, \theta_0^d + \sum_{n=1}^{n_{\max}} \theta_n^d(n) \, 1_{jmt}(n) + \theta_\ell^d \, s_{jmt}^\ell + \theta_Q^d \, \ln Q_{jt}^d + \eta_{jmt}^d$$

$$y_{jmt}^\ell = \mathbf{z}_{mt}' \, \theta_0^\ell + \sum_{n=1}^{n_{\max}} \theta_n^\ell(n) \, 1_{jmt}(n) + \theta_\ell^\ell \, s_{jmt}^d + \theta_Q^\ell \, \ln Q_{jt}^d + \eta_{jmt}^\ell$$

(29)

where $y_{jmt}^d \equiv y\left(s_{jmt}^d, s_{0mt}^d\right)$, $y_{jmt}^\ell \equiv y\left(s_{jmt}^\ell, s_{0mt}^\ell\right)$, $1_{jmt}(n) \in \{0, 1\}$ is the binary variable that indicates that the number of branches n_{jmt} is 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 have used the following approach. First, we postulate that the the market sizes H_{mt}^d and H_{mt}^ℓ are proportional to the total population in county m at period t:[23] $H_{mt}^d = \lambda^d\ POP_{mt}$ 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 $\sum_{m=1}^M s_{jmt}^d = Q_{mt}^d / H_{mt}^d$ and $\sum_{m=1}^M s_{jmt}^\ell = Q_{mt}^\ell / H_{mt}^\ell$ 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.

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 in this way of determining market size, 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 (2017), 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. Since the HMDA data do not allow us to identify individual applicants, then, although we know the number of applications, 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) Dealing with endogeneity. In the structural equations in (29), regressors s_{jmt}^ℓ, s_{jmt}^d, and $\ln Q_{jt}^d$ are endogenous variables of the model, and therefore they are correlated with the error terms η_{jmt}^d and η_{jmt}^ℓ because of simultaneity. Furthermore, though the number branches n_{jmt} is not an

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

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 (2016). 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 (2015) 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 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 bank active.

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_{jmt}^d and η_{jmt}^ℓ have the following component structure:

$$\eta_{jmt}^d = \eta_{jm}^{d(1)} + \eta_t^{d(2)} + \eta_{mt}^{d(3)} + \eta_{jt}^{d(4)} + \eta_{jmt}^{d(5)} \tag{30}$$

$\eta_{jm}^{d(1)}$ represents bank-county fixed effects; $\eta_t^{d(2)}$ represents national level unobserved shocks; $\eta_{mt}^{d(3)}$ is county-year idiosyncratic shock; $\eta_{jt}^{d(4)}$ represents a bank-year idiosyncratic shock; and $\eta_{jmt}^{d(5)}$ 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 $\eta_{jmt}^{d(5)}$ and $\eta_{jmt}^{\ell(5)}$, i.e., for any pair of markets (m, m') and any pair of years (t, t'), we have that $\mathbb{E}\left(\mathbf{z}_{mt}\ \eta_{jm't'}^{d(5)}\right) = 0$ and $\mathbb{E}\left(\mathbf{z}_{mt}\ \eta_{jm't'}^{\ell(5)}\right) = 0$. ■

Assumption ID-3: Bank-county-year shocks $\eta_{jmt}^{d(5)}$ and $\eta_{jmt}^{\ell(5)}$ 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 $\eta_{jt}^{d(4)}$ and $\eta_{jt}^{\ell(4)}$, i.e., for any market m and bank j pair, we have that $\mathbb{E}\left(\mathbf{z}_{mt}\,\eta_{jt}^{d(4)}\right) = 0$. ∎

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, $\eta_t^{d(2)}$, and the county-year idiosyncratic shock, $\eta_{mt}^{d(3)}$, from the error term. Second, a time difference between the equations at two consecutive periods. This transformation eliminates the bank-county fixed effect, $\eta_{jm}^{d(1)}$, from the error term. That is,

$$\Delta \widetilde{y}_{jmt}^d = \Delta \widetilde{\mathbf{x}}_{jm}^d\,\theta^d + \Delta \widetilde{\eta}_{jt}^{d(4)} + \Delta \widetilde{\eta}_{jmt}^{d(5)}$$
$$\Delta \widetilde{y}_{jmt}^\ell = \Delta \widetilde{\mathbf{x}}_{jm}^\ell\,\theta^\ell + \Delta \widetilde{\eta}_{jt}^{\ell(4)} + \Delta \widetilde{\eta}_{jmt}^{\ell(5)}$$

(31)

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:

$$\Delta \widetilde{y}_{jmt}^{*d} = \Delta \widetilde{\mathbf{x}}_{jm}^{*d}\,\theta^d + \Delta \widetilde{\eta}_{jmt}^{*d(5)}$$
$$\Delta \widetilde{y}_{jmt}^{*\ell} = \Delta \widetilde{\mathbf{x}}_{jm}^{*\ell}\,\theta^\ell + \Delta \widetilde{\eta}_{jmt}^{*\ell(5)}$$

(32)

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:

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

(33)

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 $\{n_{jmt}, s^d_{jmt}, s^\ell_{jmt}\}$ 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):

$$
\begin{aligned}
\mathbb{E}\left(\mathbf{z}_{m't}\left[\Delta\widetilde{\eta}^{d(4)}_{jt} + \Delta\widetilde{\eta}^{d(5)}_{jmt}\right]\right) &= 0 \\[4pt]
\mathbb{E}\left(\mathbf{z}_{m't}\left[\Delta\widetilde{\eta}^{\ell(4)}_{jt} + \Delta\widetilde{\eta}^{\ell(5)}_{jmt}\right]\right) &= 0
\end{aligned}
\tag{34}
$$

These moment conditions identify the parameters θ^d_Q and θ^ℓ_Q. 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 $m' \in \mathcal{M}^d_{jt}\}$, to instrument the total amount of deposits $\ln Q^d_{jt}$. 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 $\Delta\widetilde{\eta}^{d(4)}_{jt} + \Delta\widetilde{\eta}^{d(5)}_{jmt}$, 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 (Arellano And Bond, 1991, Arellano and Bover, 1995, and Blundell and Bond, 1999). We apply a two-step optimal GMM estimator and obtain standard errors robust of heterocedasticity and serial correlation.

6   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 above, 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 (29) 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 θ parameters are not directly comparable because they are measured in different util units since the variance of extreme value unobservables can be different in the demands for loans and deposits, i.e., α^d and α^ℓ can be different.

Nevertheless, the dependent variables in the left-hand-side of the equilibrium equations are very close to logarithm of county-level market shares, $\ln(s_{jmt}^d)$ and $\ln(s_{jmt}^\ell)$. Therefore, we make some comparisons between the θ parameters of the two equations by interpreting these parameters 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. However, 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. But 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, such that they support 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 very 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%

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.

(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 very 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 ≤ 19	-0.9071 (0.5175)	-
Share Population age ≥ 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

7 Counterfactual experiments

Using the estimated model, we implement counterfactual experiments to measure the effects home-bias, branch networks, and local market power have on the geographic segregation of deposits and loans. 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 segregation index, SI, that we have defined in equation (10) and whose evolution we presented in Figure 7; 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 represent 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 segregation 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 segregation index declines very 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 very 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 it has benefited specially larger/richer counties with a stronger demand for credit.

Experiment 2. In this experiment, we study the effects of eliminating the home bias due to economies of scope between deposits and loans. In this experiment, 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 segregation 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 segregation 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%. This tax reduces the segregation index 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 this experiment, a tax on deposits is not geographically neutral, but it 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 segregation 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.
Segregation 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).

8 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 *segregation 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 for deposits and loans in multiple geographic 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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9 Appendix

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 A**:

Table A**		
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.[24]

Using the combination of RID and agency code as shown in Table A**, HMDA institutions can be matched with SOD institutions at the bank-county-year level. Doing so generates our matched sample. Figure A** and A** show the relative importance of the matched and unmatched samples on both the loan side and the deposit side.

Figure A** 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. Table A** reports the comparison between these unmatched banks and the matched banks in 2004. Consistent with the criteria reported in Avery et. al. (2007), banks that are not obliged to report

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[24]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.

to HMDA are (1) small (as can be seen in Table A** from the amount of assets,[25] 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 A**), or (3) have offices exclusively in rural (nonmetropolitan) 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.
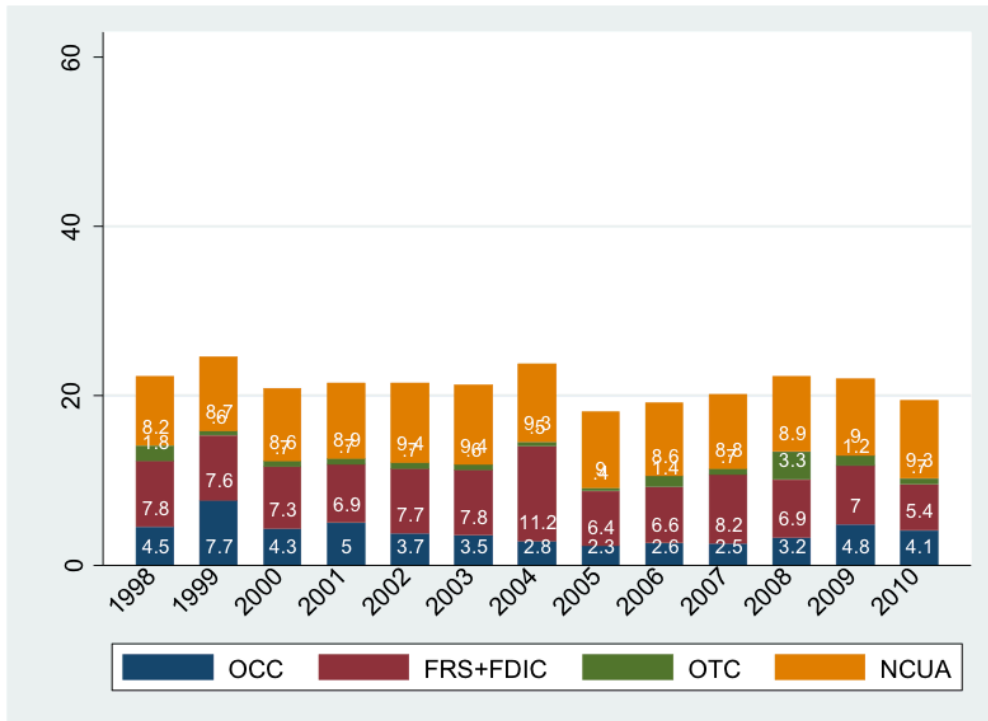
Table A**

	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 A2 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, or the "shadow banks". Our model explicitly model both the decision of the matched sample and these shadow banks. Before year 2006, the "shadow banks" contribute about 50% of the total credits. Since 2007, their contribution dropped to less than 40%, which reflect the changes since the financial crisis.
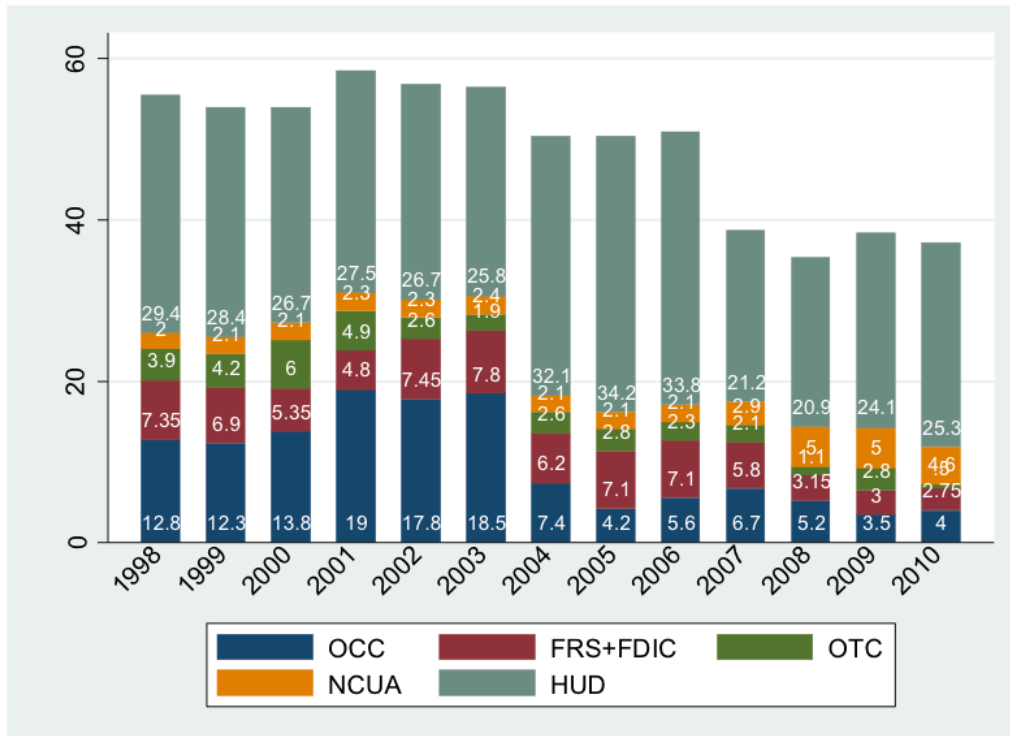
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[25]Most banks in the matched SOD sample in 2004 have assets greater than $300 million, which is consistent with the asset criterion for reporting to HMDA in that year.

Figure 8: Percentage of Deposit of Unmatched – SOD and HMDA Samples

(a) Unmatched SOD

(b) Unmatched HMDA

9.2 Additional Tables and Figures

Figure 9: Segregation Indexes between Deposit and Loan Distributions–Bank level, with *market* measured at the State level
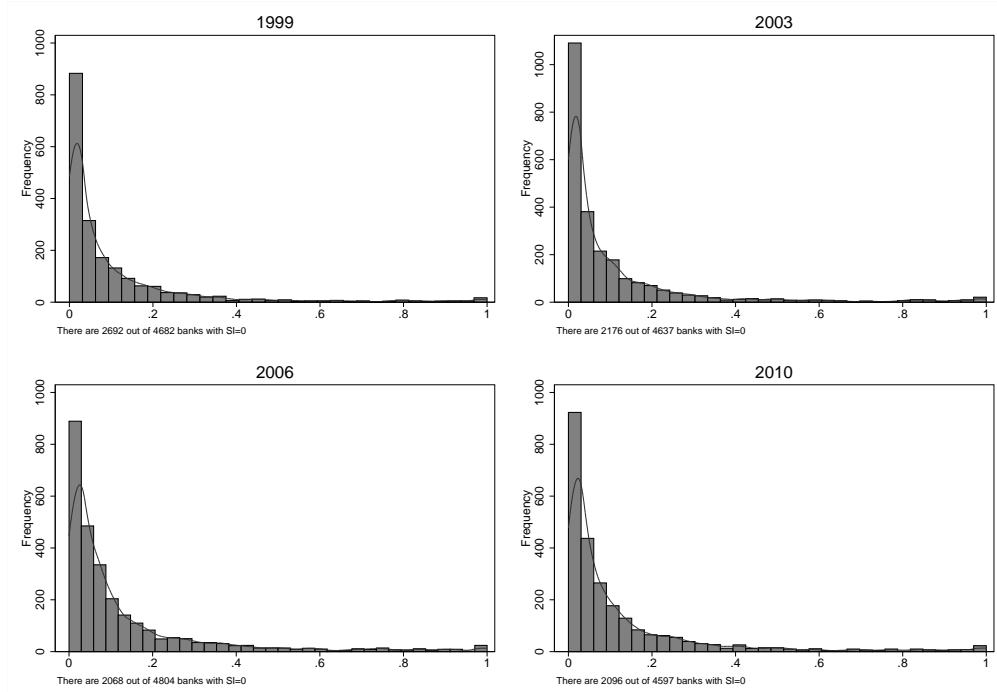

Table A1
Evolution of the segregation index of the top 10 banks (by assets)

Rank by Avg. Asset	Bank Name	SI_{1999}	SI_{2004}	SI_{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

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