Banks in Space*

Ezra Oberfield
Princeton University

Esteban Rossi-Hansberg
University of Chicago

Nicholas Trachter
FRB of Richmond

Derek Wenning
Princeton University

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Abstract

We study the spatial expansion of banks in response to banking deregulation in the 1980s and 90s. During this period, large banks expanded rapidly, mostly by adding new branches in new locations, while many small banks exited. We document that large banks sorted into the densest markets, but that sorting weakened over time as large banks expanded to more marginal markets in search of locations with a relative abundance of retail deposits. This allowed large banks to reduce their dependence on expensive wholesale funding and grow further. To rationalize these patterns we propose a theory of multi-branch banks that sort into heterogeneous locations. Our theory yields two forms of sorting. First, span-of-control sorting incentivizes top firms to select the largest markets and smaller banks the more marginal ones. Second, mismatch sorting incentivizes banks to locate in more marginal locations, where deposits are abundant relative to loan demand, to better align their deposits and loans and minimize wholesale funding. Together, these two forms of sorting account well for the sorting patterns we document in the data.

*Oberfield: edo@princeton.edu. Rossi-Hansberg: rossihansberg@uchicago.edu. Wenning: dwenning@princeton.edu. Trachter: trachter@gmail.com. We thank Anil Kashyap, Adrien Matray, and Moto Yogo, as well as participants at numerous seminars and conferences for their feedback. The views expressed herein are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

1 Introduction

Bank branches are ubiquitous. Most of us have one nearby, and it is probably a branch of a well-known bank. Since the early eighties, reciprocal interstate agreements and bank deregulation have resulted in roughly 50% more bank branches across the U.S., but a decline in the number of banks of more than 40%. The largest U.S. banks have grown rapidly by opening branches in more counties across the country, while small banks have declined and exited. This spatial expansion is marked by specific spatial sorting patterns. In this paper, we document the evolution of spatial sorting in the banking industry in response to banking deregulation, and the resulting spatial expansion of large banks, and provide a theory that rationalizes these patterns. Ultimately, local bank competition, and therefore the local access costs and interest rates individuals and firms get for their savings and pay for their loans, are determined by these patterns.

In 1981, banks could only operate in their home state and, in some instances, only in their home county. By 1996 these restrictions had changed dramatically. Voluntary reciprocal inter-state agreements implied that banks could operate in all U.S. states. In 1997 federal regulation eliminated all branching location restrictions. The largest 1% of banks took advantage of deregulation by expanding the number of branches rapidly both in terms of branches per county and, especially, by entering new counties. In contrast, many smaller banks exited or contracted their number of branches.[1]

In 1981, the largest U.S. banks were sorted into the densest counties only, while smaller banks served smaller, more rural, locations. This sorting pattern was very pronounced. Furthermore, denser counties exhibited a larger demand for loans relative to the supply of deposits, so these large banks tended to fund their lending using wholesale funding (Federal Reserve funds, time deposits, or brokered deposits). We show that the top 1% of banks used brokered deposits and Fed funds much more intensively. Because this credit is unsecured, it tends to be more expensive than retail deposits. Back in 1981, however, large banks could not enter other less dense counties where retail deposits were more abundant and demand for loans smaller.

Deregulation allowed large banks to expand geographically and they took full advantage. Where did they open new branches? The answer is nuanced. On one hand, large banks kept sorting into the larger markets in other states, but without steering too far from their headquarters, as this would have increased their operational costs. Indeed, we show that distance to headquarters explains, in part, the evolution of a bank's branching locations. However, sorting became weaker as large banks also expanded into less dense markets in search of retail deposits. We not only document this decrease in sorting in response to deregulation, but we show that the reliance of large banks on wholesale funding declined markedly in response. The ability of large banks to both operate in the largest markets, but without relying on wholesale funds because of their parallel presence in smaller markets with an abundance of retail deposits, was the foundation of their growth and success. Of course, these patterns also incentivized bank-level fixed-cost investments that allowed banks to serve their customers better and at a lower cost; for example, by investing in online platforms and

[1] See Kroszner and Strahan (2014) for a review of the regulations that limited the expansion of banks and the competition among them.

information and communication technologies.[2]

Our findings underscore the presence of two forms of sorting. The first form of sorting results from span-of-control management costs. Large productive banks face relatively large costs from locating branches in small markets because they consume management time that could be dedicated to other more profitable locations. Those profitable locations entail larger fixed costs in terms of rents and other local costs, but they also yield higher revenue. Productive banks care relatively less about these local fixed costs and more about the implied span-of-control costs of an additional branch. In contrast, small banks care more about the local costs, since the span-of-control costs are small or negligible since they only manage a small number of branches. The result is a span-of-control sorting pattern, as in Oberfield et al. (2024), that leads productive banks to locate in the densest markets with the largest local costs, but for small banks to have a larger presence in the smaller markets.

The second form of sorting is more specific to the banking industry. Consider this, admittedly enormously simplified, view of a bank's operation. A bank's business is to lend money at a relatively high interest rate and fund these loans with deposits for which it pays a relatively low interest rate. The interest rate differential determines the bank's profits after covering the costs associated with the bank's operation, as well as other costs related, for example, to the fact that deposits can be withdrawn at any time while loans have fixed terms, and the risk of default involved in lending. When a bank's loans are larger than its retail deposits, banks can use wholesale funding to fund the gap. These funds are more expensive as they command a higher interest rate, and so part of a bank's objective is to minimize their use. Because demand for loans and supply of retail deposits varies across space, banks whose operation uses wholesale funding intensively want to enter locations with large supplies of retail deposits and low demand for loans. We show that large productive banks use more wholesale funding, and, in response to deregulation, entered smaller locations than the ones in which they already had a presence, locations that were less dense and had a large supply of retail deposits.[3] Hence, this form of spatial "mismatch sorting," used to balance deposits and loans, tended to decrease the overall sorting of large banks in the densest locations.

The model we propose provides a general theory of the sorting of heterogeneous banks' branches across heterogeneous locations that generates, as an outcome, both sorting patterns: span-of-control sorting and mismatch sorting. Our starting point is the framework in Oberfield et al. (2024), which studies the equilibrium sorting of multi-plant firms in space and also generates span-of-control sorting, whereby the most productive firms locate more plants in the more expensive markets, but fewer plants in the markets with lower rents. Here, we add many new features that are relevant for the banking industry, and potentially other industries as well, including distance to headquarters costs, investments that improve a firm's appeal to customers and lead to increasing returns, and most importantly, a demand for loans and bank deposits

[2] To document these facts we use data on individual banks' branches and their deposits from The Federal Deposit Insurance Corporation (FDIC)'s Summary of Deposits from 1981 to 2006. We also collect information on bank-level wholesale funding from the Report of Condition and Income and for county-level population and per-capita income from the U.S. Census and the BEA.

[3] For a recent example of banks expanding their branch network in the search for deposits see "America's Biggest Bank Is Growing the Old-Fashioned Way: Branches" (David Benoit, *Wall Street Journal*, February 6, 2024.)

that varies differentially across locations.

Locations house an exogenous set of individuals (households and firms in other sectors) with heterogeneous preferences for banks. Traveling to a bank branch is costly, and potentially differentially costly depending on whether the customer is managing deposits or obtaining a loan. Thus, individuals prefer to bank at a branch nearby. The appeal of a bank to customers depends on the customer's distance to the bank's headquarters, idiosyncratic factors specific to a location, and bank investments to improve the appeal of its services (e.g. investments in online platforms or advertising). Consumers use the bank branch that maximizes their utility given the loan and deposit interest rates, their local and idiosyncratic appeal, and their distance.[4] They can potentially choose different banks and branches for deposits and loans.

A bank's problem, conditional on the residual demand that they face for loans and deposits in every location, is then to choose the set of branches to set up given a local fixed cost per branch and a span-of-control that depends on the total number of branches of the bank, how much to invest in deposit and loan appeal, as well as the interest rate for deposits and loans in all locations, to maximize profits.[5] Importantly, if the total deposits it receives do not cover the total amount of loans it issues, then it needs to cover the gap with unsecured wholesale funding. The cost of wholesale funding is increasing in the size of the gap relative to total deposits. Our first result shows that banks want to set interest rates for loans and deposits that are common across locations. This is consistent with Begenau and Stafford (2022) who find that banks predominantly set uniform deposit rates across branches.

The core of the model is the location decisions of a bank's branches. This is a hard combinatorial problem that cannot be solved practically for the more than 3000 counties in the U.S. Hence, as in Oberfield et al. (2024) we study the limit problem where the fixed and span-of-control costs of setting branches converge to zero, and the cost of traveling to a branch becomes large. The limit can be characterized by the density of branches that a bank sets in every location. Importantly, in this limit, all the relevant forces (cannibalization, span-of-control costs, transport costs, etc.) are still active and determine the optimal bank choices. We provide an algorithm to solve the branch location problem, a key input to solve for the monopolistically competitive equilibrium of the model.

Our two main propositions show that this framework generates the two types of sorting consistent with the deregulation experience of the U.S. banking industry. Furthermore, because banks that expand have larger incentives to invest in customer appeal, our framework also explains the large expansion in the number of branches of the most productive banks.

The empirical banking literature has established the importance of distance to a bank's branches for customers' access to banking services. For small business lending, Berger et al. (2005) show that the distance between a small firm and the bank branch it borrows from is small and that the average distance falls if the

[4] As Sakong and Zentefis (2023) document, although online and mobile banking has increased in importance in the last two decades, branches are still an important access point for banking services. They cite several surveys that show that most bank customers continue to visit branches regularly to open accounts and obtain loans and that customers tend to use branches that are close to them.

[5] We incorporate market power in the market for retail deposits following the recent literature on the deposits channel of monetary policy, e.g., Drechsler et al. (2017) and Di Tella and Kurlat (2021).

lender has more local branches.[6] Using data from the recent fracking boom, Gilje et al. (2016) argue that distance is also important in mortgage markets.[7] For deposits, Sakong and Zentefis (2023) use a gravity equation and cellphone geolocation data to estimate the impact of distance on bank use and find a coefficient on log distance in the range of -1.45 to -1.26, implying that a doubling of distance reduces the use of a branch by a factor of roughly 2.5.

In light of this evidence, and even though the main component of this important deregulation episode was the geographic expansion of the top banks, most theories of the banking sector do not incorporate space or the decision to locate bank branches across locations.[8] This is natural, given that solving spatial multi-plant location problems in equilibrium is complicated. As discussed above, we expand the methodology proposed by Oberfield et al. (2024) to the banking sector. Recently, some papers have started to study spatial issues in the banking sector. For example, Ji et al. (2023) studies the dynamic expansion of banks in Thailand and its impact on inequality. d'Avernas et al. (2023) study the location of branches of small and large banks across space and the rates they charge given the different sets of consumers that they serve. Koont (2023) studies how banks' investments in digital platforms affect the network of branches and local and aggregate concentration in the banking industry. Aguirregabiria et al. (2016) and Corbae and D'Erasmo (2020, 2021, 2022) propose models of location choice with diversification as the core reason for bank expansion, a mechanism we abstract from in this paper.[9]

Understanding the location of bank branches through the two forms of sorting that we highlight is, we believe, novel to our work. Beyond the banking industry, several studies have discussed the spatial expansion of multi-plant firms including Rossi-Hansberg et al. (2021), Hsieh and Rossi-Hansberg (2022), and Cao et al. (2019). Location choices of multiplant firms has been studied more in the international context for multinational firms, as in Tintelnot (2016) or Antràs et al. (2017), and more recently in a series of papers using the algorithm in Arkolakis et al. (2017). Still, it remains challenging to expand this type of analysis in spatial setups with many locations, and the resulting quantitative exercises do not provide the type of analytical characterization of the sorting patterns we aim to provide.

Several papers have modeled the sorting of single-plant firms only, as in Baldwin and Okubo (2006), Nocke (2006), Gaubert (2018), and Ziv (2019).[10] These papers have been motivated by the observation

[6] Using data from a cross-section of the National Survey of Small Business Finance in 1993 they estimate a mean distance of 26 miles and a median distance of only 3 miles. Petersen and Rajan (2002) use the same data along with the age of lending relationships to show that distance to lenders rose between the 1970s and 1990s, although Brevoort et al. (2010) use later waves to show that the trend has not continued past 1998. Agarwal and Hauswald (2010) provide evidence that distance makes the collection of soft information on borrowers more difficult. Nguyen (2019) uses quasi-experimental variation in bank branch closures following mergers and finds a bank branch closure reduces local small business lending across all lenders, but the effects dissipate within six miles.

[7] They study banks that were exposed to liquidity inflows from fracking booms. These banks increase mortgage originations in non-fracking counties where they had branches, but not in non-fracking counties where they did not have a presence.

[8] Kroszner and Strahan (2014) provides a recent survey.

[9] These papers build on the findings of Levine et al. (2021) who showed that when expansion increased diversification, it reduced bank volatility and the cost of funds. Morelli et al. (2023) take location choice as given and study the interplay of diversification and market power.

[10] See also Bilal (2023); Lindenlaub et al. (2022); Mann (2023); Oh (2023). Wenning (2023) models the sorting of multi-region

that plants in more dense locations tend to be more productive. As discussed in Combes et al. (2012), this cross-sectional pattern could be driven by local agglomeration effects or characteristics, sorting, or selection. Because plants do not typically move, it is difficult to find a model-consistent way to distinguish between these mechanisms using only single-plant firms. Oberfield et al. (2024) incorporates multi-plant firms and uses information about a firm's other plants together with leave-out strategies to detect sorting. Still, this strategy relies only on cross-sectional patterns. In contrast, the banking deregulation episode we study here provides a rare window into the forces driving sorting. It provides a natural experiment where we can study the establishment of branches by banks with the same origin but different sizes when a new bilateral agreement between states is signed. The results underscore the importance of the two types of sorting we have uncovered.

The rest of the paper is organized as follows. The next section introduces our data and discusses some of the key institutional details of the deregulation of banks in the 1980s and 90s. It also presents some basic patterns of the expansion of banks during this period. Section 3 introduces our theory and the limit economy we study and characterize. It also presents our presents our main results on sorting. Section 4 presents evidence showing that the two forms of sorting we uncover account well for the spatial evolution of the banking industry in response to banking deregulation. Section 5 concludes. An Appendix presents all the proofs, additional characterizations and derivations, additional empirical results, and details of the dataset construction.

2 Data, Institutional Setting, and Basic Empirical Patterns

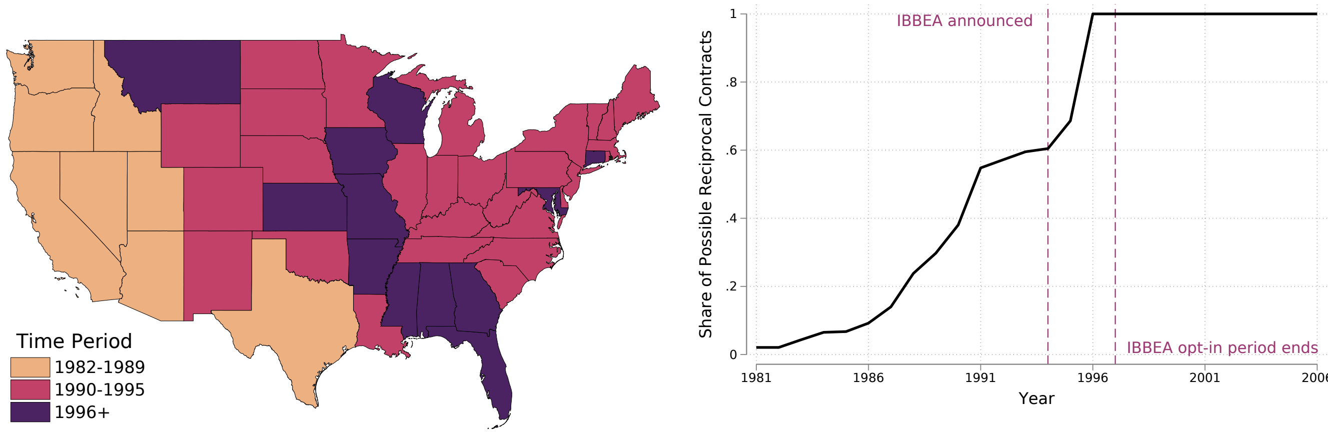
2.1 Institutional Setting: the Bank Deregulation of the 1980s and 90s

The McFadden Act of 1927 marked the onset of geographic banking regulation in the United States. Before the Act, two types of banking institutions existed: national banks, chartered by the federal government and required to operate out of a single branch, and state-chartered banks, which in some states were permitted to branch throughout the state that provided their charter (Preston, 1927). The McFadden Act was designed to take market power away from the then-dominant state-chartered banks by allowing national banks to expand within states. National banks acted swiftly. For example, Bank of Italy — at the time a single-branch, nationally-chartered operation based in San Francisco — had begun to build on its initial success by establishing state-chartered subsidiaries throughout the state of California under its holding company, Bancitaly. Following the passage of the McFadden Act, Bank of Italy merged with its subsidiaries and became Bank of America. By 1930, Bank of America had 453 branches throughout the state of California.[11]

The McFadden Act explicitly restricted banks from growing outside of their chartered state. However, many banks exploited a loophole in the regulation: the law applied only to the bank itself but did not refer

insurance firms across locations, with an emphasis on how these decisions are affected by uniform pricing rules.

[11]See Board of Governors of the Federal Reserve System (U.S.). Committee on Branch, Group, and Chain Banking, 1935 (1932).



(a) Available States that CA Banks Could Enter

(b) Reciprocal Inter-state Agreements Over Time

Figure 1: This figure shows the evolution of geographic deregulation. Panel (a) shows a map of the states available for California banks to enter between 1982 and 2006. Panel (b) shows the time series of the share of reciprocal interstate agreements across the United States.

to broader forms of organization. This prompted the creation of "group banks" — the historical term for bank holding companies — that purchased majority shares in state-chartered banks nationwide, as described in Mahon (2013). For example, through its holding company Transamerica Corporation, Bank of America quickly acquired banks throughout western U.S. states (Los Angeles Times, 1958).

In 1956, the Bank Holding Company Act of 1956 prevented further geographic expansion.[12] Existing multi-state banks were forced to part with their out-of-state branches and continue operations solely in their chartered state. Bank of America, for example, lost ownership of its western U.S. banks and became confined by the borders of California.[13]

Banks remained tethered to their home states until the late 1970's. In 1978, Maine announced it would open its borders to out-of-state banks on a bilateral reciprocal condition: if Maine opened to New York banks, for example, New York had to allow Maine banks to enter New York as well. No other states reciprocated until New York did in 1982, after which several others followed suit. We show the evolution of the reciprocal agreements in Figure 1.[14] In Figure 1a, we provide an example of the evolution of permissible out-of-state entry for California banks. States in yellow opened early to California's banks, while states in dark violet only opened by 1996 when all states liberalized. Clearly, bilateral agreements followed a spatial pattern, with neighboring and nearby states signing bilateral agreements early with California.

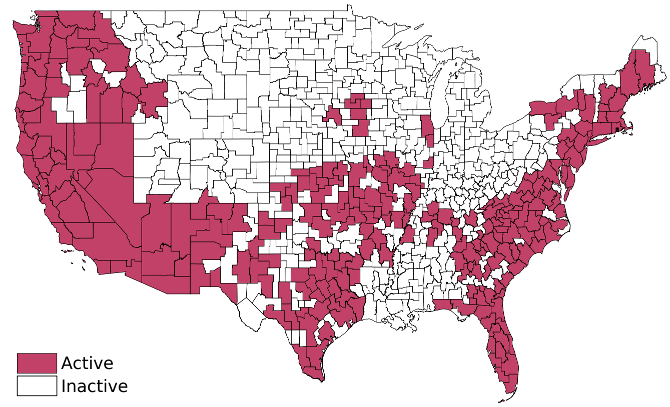
Figure 1b plots the share of active reciprocal contracts out of all possible reciprocal contracts in the contiguous U.S. over time. Starting with Maine and New York in 1982, the number of agreements increased

[12] The Bank Holding Company Act of 1956 was, however, enacted primarily to separate banks from other financial institutions such as insurance. See Bank Holding Company Act of 1956 (1956) for more details.

[13] Its 329 out-of-state domestic banks were consolidated into one entity, Firstamerica Corp. This is one of a rare number of cases where banking regulators approved out-of-state banking prior to the 1980's (Los Angeles Times, 1958).

[14] Information on the precise reciprocal contracts comes from Amel (1993).

(a) Active Bank of America Commuting Zones, 1981



(b) Active Bank of America Commuting Zones, 2006

Figure 2: This figure highlights the initial geographic restrictions and subsequent expansion of Bank of America from 1981-2006 across US commuting zones. Panel (a) shows a map of commuting zones in which Bank of America had at least one branch in 1981, and Panel (b) shows the corresponding map for 2006.

exponentially until 1991 when about half of all potential agreements had been signed.[15] The reciprocal agreements, as well as the contemporaneous relaxation of intra-state banking and branching regulation, marked the beginning of the end of the strict regulatory hold on geographic expansion in the banking industry. Inter-state banking restrictions effectively ended with the passage of the Riegle-Neal Act of 1994, also known as the Interstate Bank Branching Efficiency Act (IBBEA). The IBBEA declared that by 1997, every state would be required to permit out-of-state acquisitions, but gave states the chance to opt in prior to 1997.[16] Every state opted in by 1996, as shown in the sharp increase in reciprocal agreements in Figure 1b.

In the 1980s and 90s some banks took advantage of their ability to expand. Bank of America is a good example of the binding nature of the geographic restrictions in banking regulation. In Figure 2 we depict the evolution of its presence across commuting zones.[17] In 1981, California, Bank of America's headquarters state, did not have any reciprocal entry arrangements with other states; as a result, Bank of America was restricted to bank solely in California (Figure 2a). Hence, Bank of America operated in only 18 of 722 US commuting zones in 1981, all of California's commuting zones, serving approximately 10% of the US population. California opened up gradually to nearby states throughout the 1980s and subsequently formed reciprocal relationships with much of the eastern and central United States through the early 1990s, as shown in Figure 1a. Bank of America grew rapidly throughout this period: by 2006 (Figure 2b), Bank of

[15]The temporary slowdown in agreements in 1991 was not the result of additional institutional changes but rather the slowdown of national and regional agreements after several states had decided to deregulate nationally while other states had yet to start the process.

[16]States were permitted to limit the extent of out-of-state entry, e.g. by setting deposit caps on out-of-state banks or by limiting entry through branching. In our analysis, we consider a state to be open as long as they opt-in at all.

[17]Note that though our analysis is at the county level, we use commuting zones rather than counties for the Bank of America maps solely for visualization purposes.

America was active in 261 commuting zones, serving approximately 70% of the US population. Of course, not all banks expanded to the same extent; in fact, many banks exited the market during this period, either due to competitive forces or through consolidation.

We now proceed to describe the data we use and document some basic patterns of the spatial evolution of the U.S. banking industry during this period. These patterns guide key aspects of the theory we propose. After presenting our theory and showing the type of sorting it generates, we come back to the data and present evidence of exactly these implied sorting patterns.

2.2 Some Basic Empirical Patterns

We collect data from two primary sources. First, we collect data on individual bank branches and their deposits from The Federal Deposit Insurance Corporation (FDIC)'s Summary of Deposits from 1981 to 2006.[18] Since the historical data do not cover banks regulated by the Office of Thrift and Supervision, we exclude these banks from the analysis.[19] Each bank branch in the data has a corresponding US county code, which we use as our geographic unit of analysis.

We also collect information on bank-level wholesale funding from the Report of Condition and Income (Call Reports). We consider three types of wholesale funding: time deposits, Federal Reserve funds, and brokered deposits.

We aggregate banks to the holding company level. Before the passage of the IBBEA in 1994, holding companies that acquired out-of-state banks were required to keep the acquired banks as proper legal subsidiaries and were not permitted to convert the banks to branches of existing companies. For example, when Bank of America acquired Seafirst Corporation in Seattle in 1983, they operated Seafirst as a subsidiary of Bank of America until 1998. After 1998, Seafirst's bank identifier in the Summary of Deposits data changed to that of Bank of America, while the holding company identifier remained unchanged. Conducting our analysis at the bank level would therefore underestimate the true amount of expansion throughout the 1980s and 90s. We provide further details on the holding company data construction in Appendix B.

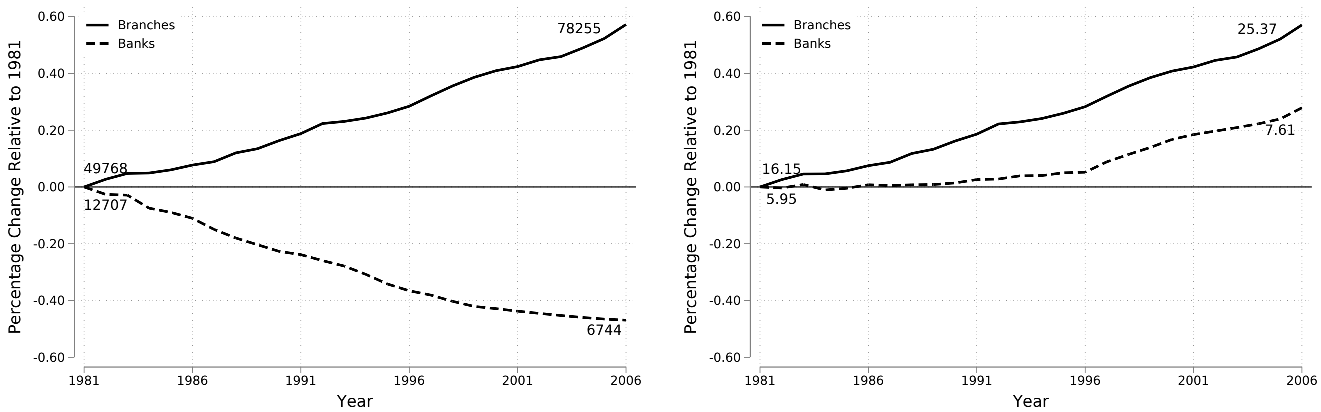
We supplement the banking data with county-level income and population measures. Population data come from the yearly county-level Census population estimates from 1980-2006. Per-capita income data come from the Bureau of Economic Analysis' EconProfile data set.

2.2.1 Basic Patterns: Fewer Banks with Many More Branches

During the deregulation period, the total number of banks declined rapidly, while the total number of bank branches increased continuously. Figure 3a documents aggregate trends in the number of banks and branches over time. The number of bank branches in the U.S. grew by nearly 60% between 1981 and 2006,

[18]The FDIC provides data from 1993 to the present. We supplement the FDIC data with historical Summary of Deposits data from 1981 to 1993 provided by Christa Bouwman.

[19]The Office of Thrift and Supervision was formed in 1989, which is why the historical data do not include banks regulated by this entity. These banks hold an average of 13% of total deposits in the United States from 1994-2006.



(a) Aggregate Banks and Branches

(b) Banks and Branches Per County

Figure 3: The evolution of total banks and total branches since 1981. The solid line shows the percentage change in the number of branches, and the dashed line shows the percentage change in the number of banks. Panel (a) shows the evolution of aggregate banks and branches, and Panel (b) displays the evolution of average banks and branches per county. Numbers reflect the initial values of branches (top) and banks (bottom) in 1981 and 2006, respectively.

while the number of banks declined by about 45%. The rapid expansion of branches per bank, particularly the large increase in the number of branches of some banks, implies that customers had access to more banks and branches in their county. Figure 3b shows that, between 1981 and 2006, the number of banks per county grew by 1.66 banks on average (28%). Even more impressive was the growth in the average number of branches per county, which grew by about 57%, as also shown in Figure 3b.[20]

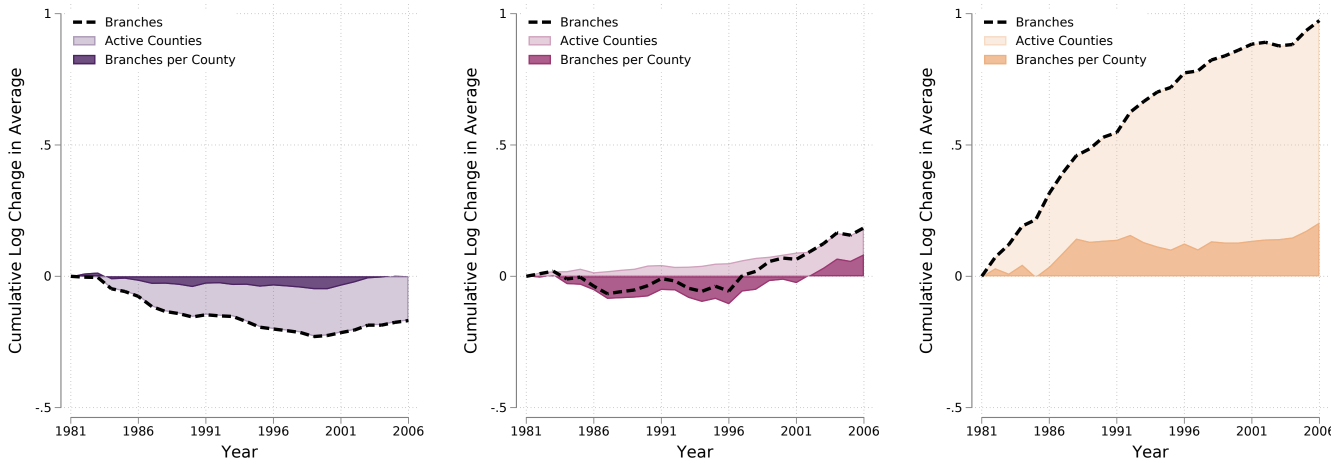
2.2.2 Basic Patterns: Top banks Expanded by Growing Geographically

We next highlight the nature of bank branch expansion across the bank size distribution. For a given size group g, in terms of total deposits, we first calculate the total number of branches in each size group. We then separate growth in the number of branches into an intensive and extensive margin, namely,

$$\Delta \log(\text{branches}_{gt}) = \underbrace{\Delta \log(\text{branches per county})_{gt}}_{\text{intensive margin growth}} + \underbrace{\Delta \log(\text{counties})_{gt}}_{\text{extensive margin growth}} .$$

The variable counties_{gt} is the total number of active counties across banks in size group g in year t. The intensive margin component measures changes in the number of branches per active county for banks in

[20]The simultaneous decline in the total number of banks and increase in the average number of banks present in a county is consistent with the findings in Rossi-Hansberg et al. (2021), which show that this is a general phenomenon across industries over the same period.



(a) Bottom 50% of Banks (b) 50-99th Percentile of Banks (c) Top 1% of Banks

Figure 4: This figure plots total branch growth for three bank size bins. The size bins are the bottom 50% of banks (Panel (a)), the 50-99th percentile of banks (Panel (b)), and the top 1% of banks by total deposits (Panel (c)) within a given year. Faded areas show extensive margin growth and solid areas show intensive margin growth. Dashed lines plot total branch growth.

group g. The extensive margin directly measures the change in the average number of active counties.[21]

Figure 4 plots the total change in branches for each size group g over time as well as the intensive and extensive margin growth components. Two patterns emerge. First, total branch growth was strongest for the largest banks: the total number of branches belonging to the top 1% of banks increased by 98 log points (166%). Branches of the bottom 50% declined by about 20 log points (-18%) relative to 1981, partly due to exit, and branches of the 50-99th percentile of banks grew by about 20 log points (22%), but only after 1996. Second, the extensive margin component dominated for all size groups. The smallest banks were crowded out or consolidated, with the entire decline coming from the extensive margin. Medium-sized banks consistently grew on the extensive margin, but only slightly. The largest banks grew on both margins, but 79% of the growth came from the extensive margin.

The fast expansion in the number of branches of top banks implied that an increasing share of all branches was concentrated in the top 1% of banks by total deposits and in banks that had a large number of branches. Figure 5 emphasizes how the top 1% of banks in total deposits grew their share of total branches. Their share essentially doubled between 1981 and 2006 and accounted for almost half of all branches by the end of the period. This was the result of a 160% increase in the total number of branches across this period for the top 1% of banks. Banks in all other size bins lost branch share, though the middle-size bins grew modestly in terms of total branches.

[21] Note that this measure controls for the overlap in branch networks across banks within a given size group. For example, if Bank of America and Wells Fargo both have branches in Los Angeles County, we count this as a single active county.

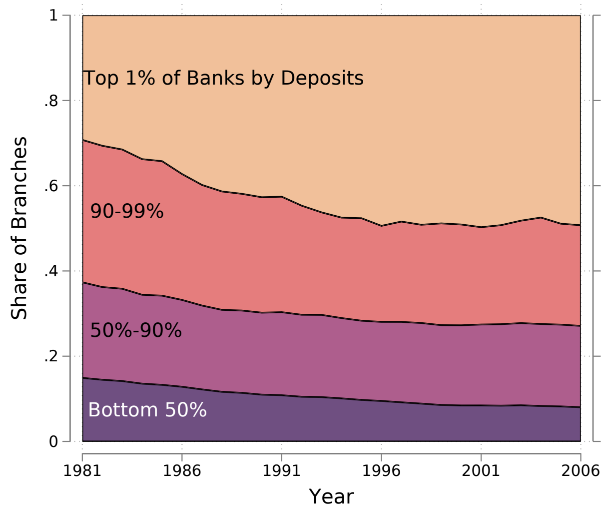


Figure 5: Branch composition by bank size over time. The size bins are percentiles of banks by total deposits within a given year. The figure shows the share of total branches by bank size bin and year.

2.2.3 Basic Patterns: Large Banks Use More Wholesale Funding

A bank's core business is to receive deposits and lend them at a higher interest rate. When there is a mismatch between deposits and loans, expensive unsecured wholesale funding may be used to bridge the gap. Wholesale funding includes brokered deposits, time deposits, and Federal Funds purchases. If banks have good business opportunities to lend but are constrained in space, they may not be able to generate enough deposits from their branches to meet loan demand. Hence, large banks might have used wholesale funding more intensively before deregulation.[22]

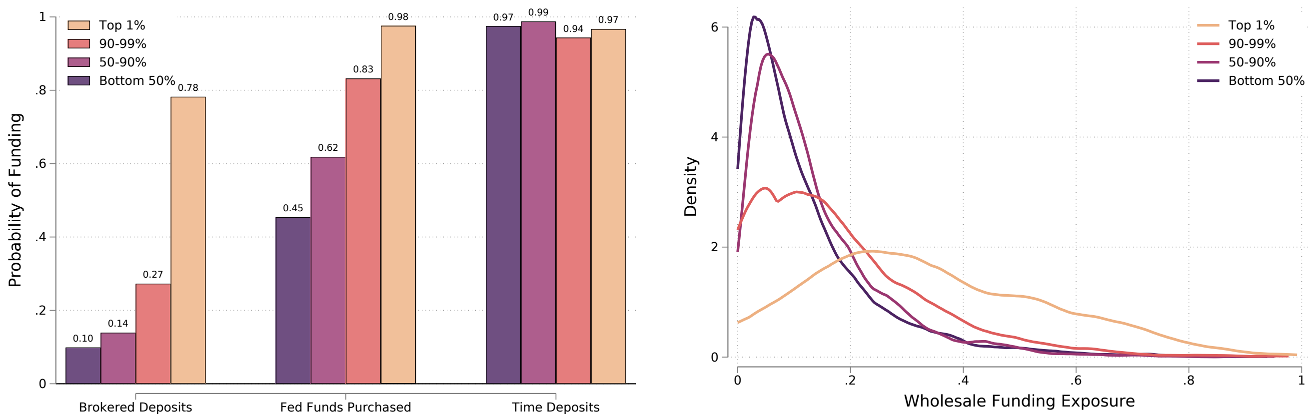
We start by documenting the use of wholesale funding across the bank size distribution in 1984. 1984 is the first period for which we have these data and marks the beginning of the deregulation period. Figure 6a shows the probability that a given bank uses a particular type of wholesale funding. Large banks are significantly more likely to use brokered deposits and Federal Funds repurchases, while slightly less likely to hold time deposits.

Figure 6b documents the distribution of wholesale funding exposure, WFE, across banks in each size bin. We measure WFE as the ratio of a bank's wholesale funds to their retail deposits, that is,[23]

$$\mathrm{WFE}_{bt} = \frac{\mathrm{FedFunds}_{bt} + \mathrm{TimeDeposits}_{bt} + \mathrm{BrokeredDeposits}_{bt}}{\mathrm{RetailDeposits}_{bt}} \tag{1}$$

[22]Geographic deregulation may therefore reduce liquidity constraints, partially explaining why reduced-form work such as Favara and Imbs (2015) finds that deregulation leads to growth in credit supply. We come back to this argument in Section 5.

[23]This value can in principle be greater than 1. However, most values above one are very small unit banks, so we exclude banks with wholesale funding greater than one from the subsequent analysis. This results in dropping 1,263 (0.6%) observations from the sample.



(a) Probability of Using Wholesale Funding

(b) Distribution of Wholesale Funding Exposure

Figure 6: The use of wholesale funds across the bank size distribution in 1984. Panel (a) shows the probability of using a particular type of funding for four bank size bins. Panel (b) shows the distribution of wholesale funding exposure within the size bins. Funding types are federal funds purchased, brokered deposits, and time deposits. Bank size bins are the bottom 50%, the 50-90th percentile, the 90-99th percentile, and the top 1% of banks by deposits.

A higher value for WFE_{bt} indicates that, conditional on a bank's size, it uses a relatively high amount of wholesale funds. Figure 6b shows that the distribution for the largest 1% of firms is much less skewed than for the bottom 99%, indicating that wholesale funding is typically used by large banks and only rarely used intensively by smaller banks.

The implication is clear: in 1984, large banks used brokerage deposits and Fed funds more often and much more intensively. This implies that the gap between retail deposits and loans was large for these banks, which made their operation less profitable. The large geographic expansion that we documented above, could therefore have been the result of the need to acquire more retail deposits. Before embarking on this and other empirical investigations we present our theory, which yields several empirical implications that guide the empirical analysis in Section 5.

3 A Spatial Theory of Banking

Consider an environment composed of banks and households that use banks for deposits and loans.[24] Space is a Jordan-measurable set $\mathcal{O}$. We consider an industry equilibrium that takes as given household locations and household demand for deposits and loans. These are held fixed in all counterfactuals. We first characterize the household decisions, which generate the local demand for deposits and loans that each bank faces. We then turn to the profit optimization problem of banks.

[24]Demand for banking services could also come from firms in other industries.

3.1 Households

Location ℓ is composed of a set of households I_ℓ. Households have heterogeneous tastes for banks and make a discrete choice over which bank and branch to use for deposits and which bank and branch to use for loans. Households dislike distance to their bank's branch. Each household in location ℓ has a taste for each bank that has a component that is common to all residents of ℓ and an idiosyncratic component. Conditional on choosing a particular bank j and branch o, the household's demand for deposits and loans depends on the interest rates set by each bank for deposits, r^D_{jo}, and loans, r^L_{jo}.

In Appendix A.1 we describe the full microfoundation of the household's problem. Here we describe the resulting residual demand curves for deposits and loans facing each bank. Households in location ℓ, who choose to use bank j for deposits, choose the branch $o^D_{j\ell} \in O_j$ that provides the best combination of distance to ℓ and interest rates, among the set of branches of bank j, O_j. Given that choice, let $r^D_{j,o^D_{j\ell}}$ be the deposit rate for bank j that is relevant for households in ℓ; namely, the deposit rate at the branch that households in ℓ choose. Similarly, let $o^L_{j\ell}$ be the branch households in ℓ would choose if they choose bank j, and $r^L_{j,o^L_{j\ell}}$ the corresponding interest rate.

Given all banks' location choices and interest rate choices, the total demand for deposits and loans from households in ℓ are given by

$$D_{j\ell} = T^D\left(\delta_{o^D_{j\ell},\ell}\right) Q^D_{j\ell} A^D_\ell \mathcal{D}\left(r^D_{j,o^D_{j\ell}}\right), \tag{2}$$

and

$$L_{j\ell} = T^L\left(\delta_{o^L_{j\ell},\ell}\right) Q^L_{j\ell} A^L_\ell \mathcal{L}\left(r^L_{j,o^L_{j\ell}}\right). \tag{3}$$

$Q^D_{j\ell}$ and $Q^L_{j\ell}$ denote common components of taste for bank j deposit and loan services among households in ℓ; $T^D(\delta)$ and $T^L(\delta)$ are decreasing functions of distance δ and summarize household distaste for distance to the bank branches it chooses for deposits and loans;[25] A^D_ℓ and A^L_ℓ are local demand shifters common to all banks which incorporate local population, local demand for deposits/loans, and local price levels/competition; $\mathcal{D}(r^D_j)$ and $\mathcal{L}(r^L_j)$ summarize the impact of interest rates on household level demand for deposits and loans, incorporating both the impact of the interest rate on the probability of choosing to use a particular bank and on the amount of deposits and loans conditional on choosing that bank.

We assume that $\mathcal{D}(\cdot)$ and $\mathcal{L}(\cdot)$ are twice continuously differentiable, that $\mathcal{D}(\cdot)$ is strictly increasing and $\mathcal{L}(\cdot)$ is strictly decreasing, that $\lim_{r\to-\infty} r\mathcal{D}(r) = \lim_{r\to\infty} r\mathcal{L}(r) = 0$, and that $\frac{\mathcal{D}\mathcal{D}''}{(\mathcal{D}')^2}$ and $\frac{\mathcal{L}\mathcal{L}''}{(\mathcal{L}')^2}$ are each strictly less than 2. These last two assumptions ensure that the unique solutions to banks' interest rate setting problems are interior.

We also assume that bank j's local appeal for each service can be decomposed into three components,

[25] The empirical literature has documented the importance of distance to bank branches for business lending (Berger et al., 2005; Petersen and Rajan, 2002)), mortgages (Gilje et al., 2016), and deposits (Sakong and Zentefis, 2023).

so

$$Q^D_{j\ell} = \bar{Q}^D_j J^D_{j\ell} \phi_{j\ell}, \tag{4}$$

and

$$Q^L_{j\ell} = \bar{Q}^L_j J^L_{j\ell} \phi_{j\ell}, \tag{5}$$

where $\bar{Q}^D_j$ and $\bar{Q}^L_j$ are common for bank j across all locations and will be determined by a bank's investment decisions; $J^D_{j\ell} \equiv J^D(\delta_{\ell^{HQ}_j,\ell})$ and $J^L_{j\ell} \equiv J^L(\delta_{\ell^{HQ}_j,\ell})$ where $J^D(\delta)$ and $J^L(\delta)$ are weakly decreasing functions of distance, to allow for the possibility that appeal is lower for locations further from bank j's headquarters at ℓ^{HQ}_j; and $\{\phi_{j\ell}\}_\ell$ are idiosyncratic appeal shifters drawn from a multivariate Frechet distribution.[26]

3.2 Banks

A bank j is born with a headquarters location, ℓ^{HQ}_j. It chooses a finite set of branch locations, O_j, and for each branch $o \in O_j$, deposit and lending rates, r^D_{jo} and r^L_{jo}. If a bank operates a branch in location o, it must pay a local fixed cost, Ψ_o. Additionally, to operate the set of branches O_j, it must hire $H(|O_j|)$ workers at its headquarters location, with H strictly increasing and strictly convex in the number of branches, $|O_j|$. Furthermore, the bank chooses the common components of bank appeal for both of its services, $\bar{Q}^D_j$ and $\bar{Q}^L_j$, by hiring $C(\bar{Q}^D_j, \bar{Q}^L_j)$ workers in its headquarters location, with C homothetic in its two arguments, strictly increasing, and strictly convex, and twice continuously differentiable. We also assume that, for any weakly positive $\bar{Q}^D$ and $\bar{Q}^L$, $C_D(0, \bar{Q}^L) = C_L(\bar{Q}^D, 0) = 0$ and $\lim_{t\to\infty} C_D(t\bar{Q}^D, t\bar{Q}^L) + C_L(t\bar{Q}^D, t\bar{Q}^L) = \infty$, where C_D and C_L denote the partial derivatives with respect to its first and second arguments respectively.[27]

Banks take deposits and make loans. They use wholesale funding to make up the gap between the two. Let

$$D_j \equiv \int D_{j\ell} d\ell \tag{6}$$

and

$$L_j \equiv \int L_{j\ell} d\ell \tag{7}$$

denote total deposits and total loans, so that the total wholesale funding required is simply $W_j = D_j - L_j$. If the bank gets funds through the wholesale market, it pays a higher interest rate on those funds than for retail deposits since wholesale funds are not insured by the federal government. The interest rate it pays on wholesale funds is $R\left(\frac{W_j}{D_j}\right)$. We assume that $R(\cdot)$ is twice continuously differentiable and weakly increasing,

[26] We provide evidence that bank appeal declines with distance from a bank's headquarters in Appendix A.5.2.
[27] Kleinman (2023) studies the role of headquarter-level investments in service firms' spatial expansion.

that $R(\omega)\omega$ is weakly convex, and that $\omega^2 R'(\omega)$ is bounded (or equivalently $\limsup_{\omega\to\infty} \omega^2 R'(\omega)$ is finite).

A bank is fully characterized by its headquarters location, ℓ_j^{HQ}, its unit costs for processing deposits and loans, θ_j^D and θ_j^L, as well as its idiosyncratic local appeal draws, $\{\phi_{j\ell}\}_\ell$. We assume the number of banks is large enough so that each bank takes the local demand shifters A_ℓ^D and A_ℓ^L as given when making pricing and location decisions. Letting w_j^* denote the wage in bank j's headquarter location, bank j's problem is thus given by

$$\pi_j = \sup_{\substack{W_j, D_j, L_j, O_j, \bar{Q}_j^D, \bar{Q}_j^L, \\ \{r_{jo}^D, r_{jo}^L\}_o, \{D_{j\ell}, L_{j\ell}, o_{j\ell}^D, o_{j\ell}^L\}_\ell}} \begin{array}{r} \int \left[(r_{j,o_{j\ell}^L}^L - \theta_j^L) L_{j\ell} - (r_{j,o_{j\ell}^D}^D + \theta_j^D) D_{j\ell} \right] d\ell - R(\frac{W_j}{D_j}) W_j - \sum_{o\in O_j} \Psi_o \\ - w_j^* H(|O_j|) - w_j^* C(\bar{Q}_j^D, \bar{Q}_j^L) \end{array} \tag{8}$$

subject to (2), (3), (4), (5), (6), (7), $W_j = D_j - L_j$, and household decisions of which branch to use.

We start our characterization of this problem by showing that each bank chooses the same interest rates for deposits and loans across all of its locations.[28] We relegate the proof of this result to Appendix A.2.1.

Lemma 1 *If bank j solves the problem in (8), it chooses to set the same interest rate on deposits across branches and the same interest rate on loans across branches. Namely, the bank chooses r_j^D and r_j^L and sets $r_{jo}^D = r_j^D$ and $r_{jo}^L = r_j^L$ for all $o \in O_j$.*

The intuition is that banks' optimal branch location already optimizes on the marginal value of a customer across locations by determining the relative distance of the closest branch, hence there is no need to additionally vary the interest rate offered. A simple corollary is that a household that uses bank j for a particular service always chooses the closest branch.

Imposing these results and changing variables so that $\omega_j \equiv \frac{W_j}{D_j}$ denotes banks j's reliance on wholesale funding, we can express firm j's problem as

$$\pi_j = \sup_{\substack{\omega_j, D_j, L_j, O_j, \bar{Q}_j^D, \bar{Q}_j^L, \\ r_j^D, r_j^L, \{o_{j\ell}^D, o_{j\ell}^L\}_\ell}} \left(r_j^L - \theta_j^L\right) L_j - \left(r_j^D + \theta_j^D\right) D_j - R\left(\omega_j\right) \omega_j D_j - \sum_{o\in O_j} \Psi_o - w_j^* H\left(|O_j|\right) - w_j^* C(\bar{Q}_j^D, \bar{Q}_j^L)$$

subject to

$$\begin{aligned} D_j &\geq \int T^D\left(\delta_{o_{j\ell}^D,\ell}\right) Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_j^D\right) d\ell, \\ L_j &\leq \int T^L\left(\delta_{o_{j\ell}^L,\ell}\right) Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_j^L\right) d\ell, \end{aligned}$$

as well as (4), (5), $(1+\omega_j)D_j = L_j$, and household decisions of which branch to use.

[28] This is consistent with Begenau and Stafford (2022) who find that banks predominantly set uniform deposit rates across branches.

Note that, since firms set the same interest across all branches, the profits of the firm depend only on its aggregate deposits and loans. The distribution of loans and deposits across branches only matters through the constraints. Of course, the collection of branches it establishes determines how binding are these constraints and therefore overall profits.

For the remainder of the paper, we study a limiting special case of the model. The special case, which we describe more formally in Appendix A.3, is one in which the local fixed cost of setting up branches as well as the incremental headquarters cost both shrink toward zero while households' distaste for distance from their branch grows large.[29] In this limiting case, it will be optimal for the firm to set up many plants. As we showed in Oberfield et al. (2024), this implies that the firm's problem converges to one in which it chooses a density n_j of branches over space, so that the density of branches bank j chooses in the neighborhood of location ℓ is $n_{j\ell}$. The firm's problem is then given by

$$\pi_j = \sup_{\substack{\omega_j, D_j, L_j, \bar{Q}^D_j, \bar{Q}^L_j, \\ r^D_j, r^L_j, \{n_{j\ell}\}_\ell}} \left(r^L_j - \theta^L_j\right) L_j - \left(r^D_j + \theta^D_j\right) D_j - \int \psi_\ell n_{j\ell} d\ell - R(\omega_j)\omega_j D_j - w^*_j h(|n_j|) - w^*_j C(\bar{Q}^D_j, \bar{Q}^L_j)$$

subject to (4), (5), $(1+\omega_j)D_j = L_j$, and

$$D_j \geq \int Q^D_{j\ell} A^D_\ell \kappa^D(n_{j\ell}) \mathcal{D}\left(r^D_j\right) d\ell, \tag{9}$$

$$L_j \leq \int Q^L_{j\ell} A^L_\ell \kappa^L(n_{j\ell}) \mathcal{L}\left(r^L_j\right) d\ell, \tag{10}$$

where $|n_j| \equiv \int n_{j\ell} d\ell$, and $\kappa^D(n)$ and $\kappa^L(n)$ are known functions that summarize the impact of additional branches on local customer appeal and depend on the distance cost functions $T^D(\delta)$ and $T^L(\delta)$, respectively. They capture the extent to which a bank offers customers branches that are close to them and takes into account the cannibalization of customers from other branches. $\kappa^D(n)$ and $\kappa^L(n)$ are strictly increasing, strictly concave, and satisfy the following properties: $\kappa^u(0) = 0$, $\lim_{n\to\infty} \kappa^u(n) = 1$, $\kappa^{u\prime}(0) \in (0,\infty)$, $\kappa^{u\prime\prime}(0) = 0$, and $1 - \kappa^u(n) \underset{n\to\infty}{\sim} n^{-1/2}$ for each use $u \in \{D, L\}$. ψ_ℓ denotes the fixed cost of setting up a unit density of plants in ℓ in the limit case and is defined in Appendix A.3. We now show that bank j's reliance on wholesale funding is a sufficient statistic for its shadow values of deposits and loans.

As we discussed above, banks are characterized by their cost of issuing loans and deposits, their headquarters location, and their idiosyncratic appeal across locations. Productive banks that have low costs earn more from issuing deposits and loans and are willing to use more wholesale funds. Similarly, banks that have more appeal in large markets, because of their location or because of idiosyncratic reasons, are willing to use more wholesale funds to satisfy their higher demand for loans. Hence, banks with more wholesale

[29] We parameterize a sequence of economies where the parameters depend on Δ and study the limiting economy as $\Delta \to 0$. The cost of distance functions are $T^D(\delta;\Delta) = t^D(\delta/\Delta)$ and $T^L(\delta;\Delta) = t^L(\delta/\Delta)$; the span of control cost is $H(|O|;\Delta) = h(\Delta^2|O|)$; the local fixed cost is $\Psi_\ell(\Delta) = \Delta^2\psi_\ell$.

funds are larger, as we showed was the case empirically in the previous section.

To see this, let λ_j^D and λ_j^L be the respective multipliers on constraints (9) and (10), namely, the shadow values of deposits and loans, respectively. The first-order conditions with respect to D_j, L_j, and ω then implies that these multipliers are given by

$$\lambda_j^D = \underbrace{R(\omega_j) + (1+\omega_j)\omega_j R'(\omega_j)}_{\equiv \rho^D(\omega_j)} - r_j^D - \theta_j^D, \tag{11}$$

and

$$\lambda_j^L = r_j^L - \theta_j^L - \underbrace{[R(\omega_j) + \omega_j R'(\omega_j)]}_{\equiv \rho^L(\omega_j)}. \tag{12}$$

The expressions are intuitive. Start with the shadow cost of a deposit in equation (11). The shadow value of an additional deposit is the value of relaxing the need for wholesale funding, $\rho^D(\omega_j)$, minus the interest rate paid, r_j^D, and the cost of processing the loan, θ_j^D. Note that the shadow value of relaxing the wholesale constraint is an increasing function of only bank j's reliance on wholesale funds, ω_j. The shadow value of an additional loan in (12) is the interest charged for the loan, r_j^L, minus its processing costs, θ_j^L, minus the costs from tightening the wholesale funds' constraint, $\rho^L(\omega_j)$, which again is an increasing function of only the bank's reliance on wholesale funding, ω_j.

The expressions for ρ^D and ρ^L also imply that $\rho^{D\prime}(\omega_j) = (1+\omega_j)\rho^{L\prime}(\omega_j)$, or

$$D_j \rho^{D\prime}(\omega_j) = L_j \rho^{L\prime}(\omega_j).$$

That is, at the optimum, the marginal contribution of wholesale funding to the shadow cost of funding loans equals its marginal contribution to the shadow payoff from deposits.

The interest rate the bank pays on deposits and the one it charges on loans depend on these shadow values, its costs, and the demand function. The first order condition for r_j^D along with equation (9) imply that

$$\begin{aligned} \mathcal{D}\left(r_j^D\right) =& \lambda_j^D \mathcal{D}'\left(r_j^D\right) \\ =& (\rho^D(\omega_j) - r_j^D - \theta_j^D)\mathcal{D}'\left(r_j^D\right). \end{aligned}$$

Similarly, the first order conditions for r_j^L together with equation (10) imply that

$$\begin{aligned} \mathcal{L}\left(r_j^L\right) =& -\lambda_j^L \mathcal{L}'\left(r_j^L\right) \\ =& -(r_j^L - \theta_j^L - \rho^L(\omega_j))\mathcal{L}'\left(r_j^L\right). \end{aligned}$$

Hence, given all fundamentals, we can determine the bank's deposit and loan interest rates using only the wholesale funds intensity of the bank. More reliance on wholesale funds raises the shadow cost of funds for lending and the shadow value of funds from deposits, as $\rho^{L\prime}(\omega) = \frac{d^2[R(\omega)\omega]}{d\omega^2} > 0$ and $\rho^{D\prime}(\omega) = (1+\omega)\frac{d^2[R(\omega)\omega]}{d\omega^2} > 0$. In addition, the second-order conditions of the interest rate problem ensure a positive pass-through of marginal cost/value of funds into interest rates.[30] As a result, higher wholesale funding ω_j leads to higher r_j^L and r_j^D, and hence higher $\mathcal{D}(r_j^D)$ and lower $\mathcal{L}(r_j^L)$.[31] We summarize these results in the following lemma.

Lemma 2 *Given its processing costs, θ_j^D and θ_j^L, a bank's wholesale funding intensity ω_j is a sufficient statistic for its deposit and lending rates, r_j^D and r_j^L, which are the unique solutions to*

$$r_j^D = \arg\max_r \left[\rho^D(\omega_j) - r - \theta_j^D\right]\mathcal{D}(r) \tag{13}$$

$$r_j^L = \arg\max_r \left[r - \theta_j^L - \rho^L(\omega_j)\right]\mathcal{L}(r). \tag{14}$$

r_j^D and r_j^L are both increasing functions of ω_j. $\mathcal{D}(r_j^D)$ is increasing in ω_j while $\mathcal{L}(r_j^L)$ is decreasing in ω_j.

A solution to a bank's problem can therefore be found using the following algorithm:

1. Guess ω_j, $\bar{Q}_j^D$, and $\bar{Q}_j^L$.

2. r_j^D and r_j^L then satisfy equations (13) and (14).

3. With interest rates we can compute the multipliers λ_j^D and λ_j^L using equations (11) and (12).

4. The optimal footprint for bank j, n_j can then be solved using the first-order conditions with respect to $n_{j\ell}$ for all locations, namely,

$$\left[\lambda_j^D Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_j^D\right) + \lambda_j^L Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_j^L\right)\right]\kappa'(n_{j\ell}) = \psi_\ell + w_j^* h'(|n_j|),$$

   where $Q_{j\ell}^D$ and $Q_{j\ell}^L$ are determined by equations (4) and (5).

5. Total deposits and loans are then given by equations (9) and (10), with equality.

6. The final step is to check whether these actions are consistent with the original guesses on wholesale

[30] Consider the deposit and lending interest rate problems $r^D \equiv \arg\max_r (c-r)\mathcal{D}(r)$ and $r^L \equiv \arg\max_r (r-c)\mathcal{L}(r)$. The pass-through of marginal cost into interest rates is $\frac{dr^D}{dc} = 1/\left(2 - \frac{\mathcal{D}(r^D)\mathcal{D}''(r^D)}{\mathcal{D}'(r^D)^2}\right)$ and $\frac{dr^L}{dc} = 1/\left(2 - \frac{\mathcal{L}(r^L)\mathcal{L}''(r^L)}{\mathcal{L}'(r^L)^2}\right)$, which are positive when the the second order conditions of the interest rate setting problems are satisfied.

[31] These results are consistent with the findings of Gilje et al. (2016), who study banks whose geographic footprint overlapped with areas undergoing the fracking boom. These banks experienced large inflows in liquidity, as deposits in those areas rose and borrowers paid down loans. They find that those banks reduced deposit rates (specifically interest expenses relative to deposits) and increased mortgages in locations that were not exposed to the fracking boom.

reliance and bank appeal, namely,

$$\begin{aligned}
\omega_j &= \frac{L_j - D_j}{D_j}, \\
\frac{\partial C(\bar{Q}_j^D, \bar{Q}_j^L)}{\partial \bar{Q}_j^D} &= \int \lambda_j^D A_\ell^D \mathcal{D}(r_j^D) \kappa^D(n_{j\ell}) J_{j\ell}^D \phi_{j\ell} d\ell, \\
\frac{\partial C(\bar{Q}_j^D, \bar{Q}_j^L)}{\partial \bar{Q}_j^L} &= \int \lambda_j^L A_\ell^L \mathcal{L}(r_j^L) \kappa^L(n_{j\ell}) J_{j\ell}^L \phi_{j\ell} d\ell.
\end{aligned}$$

We now proceed to characterize how banks set up their branches across space. Namely, we characterize the sorting patterns of bank branches.

3.3 Sorting and the Determinants of Firms' Footprints

In the model, four distinct forces determine a bank's geographic footprint. First, banks are likely to place branches close to headquarters since this directly increases their appeal. Second, "span-of-control sorting" says that more productive banks sort into denser more expensive locations, while less productive banks open branches in less attractive, but cheaper, markets. Third, "mismatch sorting" says that banks choose locations based on the match of the location's characteristics to the funding needs of the bank. We discuss each in turn in this subsection. Finally, a bank's incentives to invest in its appeal to borrowers and depositors determine the bank's size, but also the value of entering different locations. We study this last force in the final subsection.

3.3.1 Distance to Headquarters

First, banks are likely to place branches close to headquarters. This is a common feature in the multinational literature (e.g. Tintelnot (2016)), and is apparent in the clustering of a bank's establishments at locations near its headquarters. In the model, we have assumed this directly through the bank appeal functions in equations (4) and (5). Namely, bank appeal, given by $Q_{j\ell}^D$ and $Q_{j\ell}^L$, is higher when location ℓ is closer to the bank's headquarters.

3.3.2 Span-of-Control Sorting

Second, banks sort across locations with different characteristics. In particular, more productive banks are likely to place more branches in more expensive and denser locations, whereas less productive banks are likely to place more branches in cheaper, less dense, locations. This force was discussed in detail in Oberfield et al. (2024).

Define $z_j^D \equiv \lambda_j^D \bar{Q}_j^D \mathcal{D}(r_j^D)$ and $z_j^L \equiv \lambda_j^L \bar{Q}_j^L \mathcal{L}(r_j^L)$. In addition, define $\sigma_j \equiv w_j^* h'(|n_j|)$ to be bank j's marginal span-of-control cost. That is, σ_j represents the management resources required by the bank to operate an additional branch. Then the first order condition on $n_{j\ell}$ (a marginal increase in the mass of branches of bank j in location ℓ) is given by

$$\left[z_j^D J_{j\ell}^D A_\ell^D \kappa^{D\prime}(n_{j\ell}) + z_j^L J_{j\ell}^L A_\ell^L \kappa^{L\prime}(n_{j\ell})\right] \phi_{j\ell} = \psi_\ell + \sigma_j. \tag{15}$$

The left-hand side of equation (15) represents the marginal increase in profits from setting up an additional branch taking into account how it relaxes the wholesale funds' constraint (through λ_j^D and λ_j^L which determine z_j^D and z_j^L) and also how the branch cannibalizes other local branches (through $\kappa^{D\prime}$ and $\kappa^{L\prime}$). The right-hand side represents the total fixed cost of an additional branch. It includes the fixed cost of setting up the branch, ψ_ℓ, but also the marginal span-of-control costs from adding a new branch to the bank's portfolio, σ_j. This last cost is large for larger banks since, due to their higher productivity or better appeal, they set up more branches and the span-of-control cost function, $h(\cdot)$, is convex. Then, if the span of control cost rises sufficiently fast with the total number of branches, as formalized in Assumption 1 below,[32] it leads to "span-of control" sorting. We show this in the next lemma and proposition.

Assumption 1 *The marginal span of control cost $h'(\cdot)$ is uniformly more elastic than the marginal local efficiencies of branching, $\kappa^{D\prime}(\cdot)$ and $\kappa^{L\prime}(\cdot)$:*

$$\inf_{N\geq 0} \frac{Nh''(N)}{h'(N)} \geq \sup_{u\in\{D,L\},n\geq 0} \frac{-n\kappa^{u\prime\prime}(n)}{\kappa^{u\prime}(n)}.$$

Before we present our main result on "span-of-control" sorting, we show that more productive banks have higher marginal span-of-control costs, σ_j and, under Assumption 1, the difference is larger than their difference in deposit and loan productivities. All proofs are relegated to Appendix A.2.

Lemma 3 *Consider two banks with the same headquarters location and the same realization of idiosyncratic local taste shocks, $\{\phi_{j\ell}\}$. Suppose that Bank 2 is equally more productive than Bank 1 in both services, so $z_2^D/z_1^D = z_2^L/z_1^L > 1$. Then $\sigma_2 > \sigma_1$ and, if Assumption 1 holds, $\sigma_2/\sigma_1 > z_2^D/z_1^D = z_2^L/z_1^L$.*

With this result in hand, we can derive a characterization of span-of-control sorting. Intuitively, larger endogenous fixed costs make large banks sort into the most expensive locations since it makes them less sensitive to the exogenous part of their fixed costs. The next proposition establishes the result formally.

Proposition 4 *Consider two banks with the same headquarters location and the same realization of idiosyncratic local taste shocks, $\{\phi_{j\ell}\}$. Suppose that Bank 2 is equally more productive than Bank 1 in both*

[32] Note that the elasticities of the marginal efficiencies of branching are continuous and $\lim_{n\to 0} \frac{-n\kappa^{u\prime\prime}(n)}{\kappa^{u\prime}(n)} = 0$, and $\lim_{n\to\infty} \frac{-n\kappa^{u\prime\prime}(n)}{\kappa^{u\prime}(n)} = 3/2$, for $u \in D, L$. If these elasticities are each increasing with n (as in the natural case when household's distance costs are exponential, $t^D(\delta) = e^{-\tau^D\delta}$ and $t^L(\delta) = e^{-\tau^L\delta}$), then Assumption 1 reduces to an assumption that $\frac{Nh''(N)}{h'(N)}$ is bounded below by 3/2.

services so $\frac{z_2^D}{z_1^D} = \frac{z_2^L}{z_1^L} > 1$ *and that Assumption 1 holds. Among locations with the same deposit intensity* $\alpha_\ell \equiv \frac{A_\ell^D}{A_\ell^L}$*, there is a cutoff* $\bar{\psi}$ *such that*

- *if* $\psi_\ell = \bar{\psi}$ *then* $n_{2\ell} = n_{1\ell}$,
- *if* $\psi_\ell > \bar{\psi}$ *then* $n_{2\ell} > n_{1\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0, and$
- *if* $\psi_\ell < \bar{\psi}$ *then* $n_{2\ell} < n_{1\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0.$

The proposition says that, controlling for motives related to the mismatch between deposits and loans (e.g. relative firm productivities across services, $z_2^D/z_1^D = z_2^L/z_1^L$, or deposit intensity, α_ℓ), for any two banks there is a cutoff level for the exogenous fixed cost at which the two banks open the same number of branches. For locations with higher local exogenous fixed cost, the more productive bank operates more branches; for locations with lower local fixed costs, the less productive firm operates more plants. This form of sorting arises due to the span-of-control costs. While the more productive (or more appealing) bank would earn higher profits per branch in any location, the more productive firm also has a higher marginal span-of-control cost from operating an additional branch. As a result, a given percentage difference in the exogenous fixed cost across locations implies a smaller proportional change in a large bank's total fixed cost. In contrast, less productive (or less appealing) banks are less encumbered by span-of-control concerns since they operate only a small number of branches and so their marginal span-of-control cost is small.[33] Because exogenous fixed costs are related to local land rents and factor prices and these in turn are positively related to local income and population density, this prediction implies that banks sort across all these dimensions.

3.3.3 Mismatch sorting

Third, banks tend to place branches in locations where there is a good match between the funding needs of the bank and the relative demand for deposits and loans. Banks try to reduce the mismatch between deposits and loans to reduce their dependence on expensive wholesale funds. Firms that need deposits, i.e., those with high dependence on wholesale funds, are more likely to go to places that disproportionately want to use banks for deposits. We name this, we believe novel, form of sorting, "mismatch sorting".

Define the deposit intensity as in the previous proposition, namely $\alpha_\ell \equiv A_\ell^D/A_\ell^L$. The ratio α_ℓ summarizes household demand for deposits relative to loans, as well as competition from other banks. The following proposition establishes mismatch sorting.

[33] The assumptions in Proposition 4 can be weakened. $z_2^D > z_1^D$ and $\frac{\sigma_2}{z_2^D} > \frac{\sigma_1}{z_1^D}$ are necessary and sufficient for sorting. Lemma 3 showed that Assumption 1 is sufficient for the latter to hold among every pair of banks with the same headquarters and idiosyncratic shocks. A weaker condition that is sufficient for there to be sorting between two banks is that $\frac{\log h'(N_2) - \log h'(N_1)]}{\log N_2 - \log N_1}$ is larger than the upper bound on the elasticities of marginal transport costs. There are examples, such as $h(N) = N^a$ for large enough a, in which there is sorting among every pair, and examples in which the condition holds among banks larger than some threshold, e.g., $h(N) = e^{aN}$, so that there is sorting among large banks but not necessarily among small ones.

Proposition 5 *Consider two banks with the same span of control cost* $\sigma_1 = \sigma_2$ *and the same efficiency of processing deposits and loans,* $\theta_1^D = \theta_2^D$ *and* $\theta_1^L = \theta_2^L$*. Assume that Bank* 2 *is more reliant on wholesale funding than Bank* 1*, so* $\omega_2 > \omega_1$*, then*

1. *there are cutoffs* $\bar{\alpha} \geq \underline{\alpha}$ *such that*
   - *if* $\alpha_\ell > \bar{\alpha}$ *and* $Q_{2\ell}^D \geq Q_{1\ell}^D$ *then* $n_{2\ell} > n_{1\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0$*,*
   - *if* $\alpha_\ell < \underline{\alpha}$ *and* $Q_{1\ell}^L \geq Q_{2\ell}^L$ *then* $n_{1\ell} > n_{2\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0$*.*
2. *If distance for lending is the same as distance for borrowing, i.e.,* $\kappa^D(n) = \kappa^L(n), \forall n$*, then there is a single cutoff* $\hat{\alpha}$ *such that if local appeal in a location is the same across banks and uses, i.e.,* $Q_{1\ell}^D = Q_{2\ell}^D = Q_{1\ell}^L = Q_{2\ell}^L$*, then*
   - *if* $\alpha_\ell > \hat{\alpha}$ *then* $n_{2\ell} > n_{1\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0$*,*
   - *if* $\alpha_\ell < \hat{\alpha}$ *then* $n_{1\ell} > n_{2\ell}$ *or* $n_{2\ell} = n_{1\ell} = 0$*.*

The result implies that if there are two similar banks but one of them is more reliant on wholesale funding, that bank is more likely to open branches in areas with high deposit intensity, α_ℓ. For example, banks with headquarters in locations that have a high demand for loans (e.g. cities with many productive firms and high real estate costs) expand more into locations where they can collect relatively more retail deposits. That is, the branch portfolio of banks is designed, in part, to reduce the mismatch between deposits and loans.

In Section 4 we turn to the data to provide evidence of the two forms of sorting we have characterized. Before doing so we discuss how a bank's investment in its appeal to customers affects its scale and generates spillovers across branches.

3.4 Bank-Level Investments and Spillovers Across Branches

A bank can make investments that improve its appeal to depositors and borrowers. These investments entail bank-level costs that affect the appeal of all its branches and therefore are more profitable for larger banks. Naturally, as banks grow due to, say, an increase in residual demand for deposits or loans in a particular location, the resulting investments in the bank's appeal affect the bank's operations in all its locations. Hence, cross-branch spillovers are not only the result of the two forms of sorting described above but also of bank-level investments in appeal that depend on its scale.

Note that a bank's total deposits and total loans can be expressed as $D_j = \bar{Q}^D \mathcal{D}(r_j^D) B_j^D$ and $L_j = \bar{Q}^L \mathcal{L}(r_j^L) B_j^L$, where

$$B_j^D \equiv \int A_\ell^D J_{j\ell}^D \phi_{j\ell} \kappa^D(n_{j\ell}) d\ell,$$

$$B_j^L \equiv \int A_\ell^L J_{j\ell}^L \phi_{j\ell} \kappa^L(n_{j\ell}) d\ell.$$

B_j^D and B_j^L summarize a bank's geographic footprint and are sufficient (along with the processing costs θ_j^D and θ_j^L) to determine the bank's choices of appeal $(\bar{Q}_j^D, \bar{Q}_j^L)$, interest rates, total deposits, total loans, and its wholesale funding.

We now characterize how changes in a bank's demand, manifested in changes to B_j^D and B_j^L, affect a bank's investments in appeal and determine a bank's overall scale of deposits and loans. Any change in B_j^D and B_j^L can be decomposed into two components, a pure scale effect in which the two shift in proportion, and a shift in the relative demand for deposits or loans. We study the effects of each in turn.

3.4.1 Returns to Scale

Suppose that residual demand rises for both deposits and loans in some locations where a bank operates. Namely, A_ℓ^D and A_ℓ^L both increase so that, holding the firm's branch locations fixed, B_j^D and B_j^L rise by the same proportion. Proposition 6 shows that the impact on a bank's appeal and on the incentives to open branches (as summarized by z_j^D and z_j^L) can be summarized by the curvature of the cost of investments in appeal, namely,

$$\varepsilon_j^C = \left. \frac{\frac{d^2}{dt^2} C(t\bar{Q}_j^D, t\bar{Q}_j^L)}{\frac{d}{dt} C(t\bar{Q}_j^D, t\bar{Q}_j^L)} \right|_{t=1}.$$

Proposition 6 *Suppose that* $d\log B_j^D = d\log B_j^L \equiv d\log B$. *Then,*

$$d\log \bar{Q}_j^D = d\log \bar{Q}_j^L = d\log z_j^D = d\log z_j^L = d\log D_j = d\log L_j = \frac{1}{\varepsilon_j^C} d\log B,$$

and there is no change in the bank's wholesale funding intensity or interest rates.

Clearly, if the cost of appeal is close to linear, so ε_j^C is close to zero, the bank responds to increased demand by strongly scaling up its investment in appeal. In contrast, if the cost function is very convex, so ε_j^C is large, the incremental investment is minimal. Changes in the bank's incentives to operate more branches are driven solely by changes in its investment in appeal.

These arguments imply that banks whose headquarters are located in, or close to, big cities where overall residual demand is high should, all else equal, make larger investments in customer appeal. The increases in demand generated by the bank's enhanced appeal in turn increase the incentives to open more branches and invest even more in appeal. Hence, investments in bank-level appeal lead to returns to scale and exacerbate the advantage provided by market access.[34] In fact, in the deregulation episode of the 1980s and 90s, banks that started in large states, like Bank of America in California, or large cities, like Citibank or Chase in New York, ended up growing tremendously.

While the results above analyze the case of identical proportional increases in demand for deposits and loans, we now proceed to analyze the case where the increase is unbalanced.

[34] In Appendix A.5.1 we show that banks that entered with headquarters in high-density counties grew more than banks headquartered in low-density counties.

3.4.2 Specialization Through Investments vs. Mismatch Sorting

Suppose now that some locations where a bank operates increase their residual demand for loans relative to deposits so that, holding fixed the bank's branches, B_j^L rises relative to B_j^D. How does this change affect the bank's incentives to shift its footprint toward deposit-intensive or loan-intensive locations?

Mismatch sorting implies that, because more loans make the bank more reliant on wholesale funding, the bank has stronger incentives to raise deposits elsewhere and weaker incentives to make loans. Namely, $\rho^D(\omega_j)$ and $\rho^L(\omega_j)$ both rise. However, investments in appeal generate an additional effect. Namely, higher demand for loans gives the bank an incentive to increase investments in loan appeal, raising $\bar{Q}_j^L$ relative to $\bar{Q}_j^D$. Hence, through this channel, higher demand for loans in one location increases lending elsewhere.[35]

Which of these opposing forces dominates depends on three elasticities. First, the elasticity of the relative shadow value of deposits and loans $(\lambda_j^D/\lambda_j^L)$ with respect to wholesale funding intensity, given by

$$\varepsilon_j^\lambda \equiv \frac{d\log\left(\lambda_j^D/\lambda_j^L\right)}{d\log\left(1+\omega_j\right)}.$$

Second, the elasticity of the ratio of of local deposits demanded to local loans demanded with respect to wholesale funding intensity, given by ε_j^X where

$$\varepsilon_j^X \equiv \frac{d\log\left[\mathcal{D}\left(r_j^D\right)/L\left(r_j^L\right)\right]}{d\log(1+\omega_j)}.$$

Lemma 2 implies that $\varepsilon_j^X \geq 0$ and $\varepsilon_j^\lambda + \varepsilon_j^X \geq 0$, where each inequality is strict in the region where $R'(\omega_j) > 0$. Further, in the empirically relevant case of imperfect pass-through of shadow costs into interest rates, $\varepsilon_j^\lambda > 0$. Finally, the elasticity of complementarity of the cost of appeal, given by

$$\chi_j = \frac{d\log C_D/C_L}{d\log \bar{Q}^D/\bar{Q}^L},$$

where C_D and C_L denote the derivatives of $C(\cdot)$ with respect to its first and second arguments, respectively. Since $C(\cdot)$ is convex, $\chi_j \geq 0$.[36]

Proposition 7 characterizes how the bank's incentives to seek out deposits versus loans change in response to changes in B_j^L/B_j^D, as a function of these three elasticities.

Proposition 7 *A bank's profit maximization implies that*

$$d\log\frac{z_j^L}{z_j^D} = -\left[\frac{\varepsilon_j^\lambda(2+\chi_j) + \varepsilon_j^X(1+\chi_j) - 1}{\varepsilon_j^\lambda + \varepsilon_j^X(1+\chi_j) + \chi_j}\right] d\log\frac{B_j^L}{B_j^D},$$

[35] Note that this investment channel was shut down in Proposition 5 since the proposition compared banks' presence in a location conditional on their local loan and deposit appeal.

[36] For example, if $C(\bar{Q}^D, \bar{Q}^L) = \left[(\bar{Q}^D)^a + (\bar{Q}^L)^a\right]^{b/a}$, with $a, b > 1$, then $\chi_j = a - 1$.

and

$$d\log\frac{L_j}{D_j}=\left[1-\frac{\varepsilon_j^{\lambda}+\varepsilon_j^{X}(1+\chi_j)-1}{\varepsilon_j^{\lambda}+\varepsilon_j^{X}(1+\chi_j)+\chi_j}\right]d\log\frac{B_j^L}{B_j^D}.$$

Note that, if ε_j^{λ}, ε_j^{X}, and χ_j are sufficiently large, then the term in brackets in the first equation in Proposition 7 is positive, and the term in brackets in the second equation is positive but less than one. Hence, in this case, mismatch sorting dominates the specialization motive. That is, more local demand for loans increases the bank's incentives to seek out deposits (z^D rises relative to z^L), and the ratio of total loans to total deposits rises less than one-for-one with the increased demand. Intuitively, if ε_j^{λ} and ε_j^{X} are large, the augmented need for wholesale funding increases the profitability of deposits relative to loans. Namely, the mismatch sorting effect is strong. In addition, if χ_j is large, it is costly to change the bank's relative appeal. Hence, the specialization effect is weak.

A useful example of the implications of Proposition 7 is the case in which the bank makes a single investment $\bar{Q}_j$ that applies to all customers regardless of whether they seek deposits or loans. So, let $C(\bar{Q}_j^D,\bar{Q}_j^L)=\tilde{C}(\max\{\bar{Q}_j^D,\bar{Q}_j^L\})$, which implies that $\bar{Q}_j^D=\bar{Q}_j^L=\bar{Q}_j$ and an elasticity of complementarity equal to infinity, $\chi_j=\infty$. In this case, mismatch sorting always dominates, since the only shift in incentives to attract deposits relative to loans comes from changes in wholesale funding intensity. Hence, in this example, higher local demand for loans always causes the bank to seek out more deposits.[37]

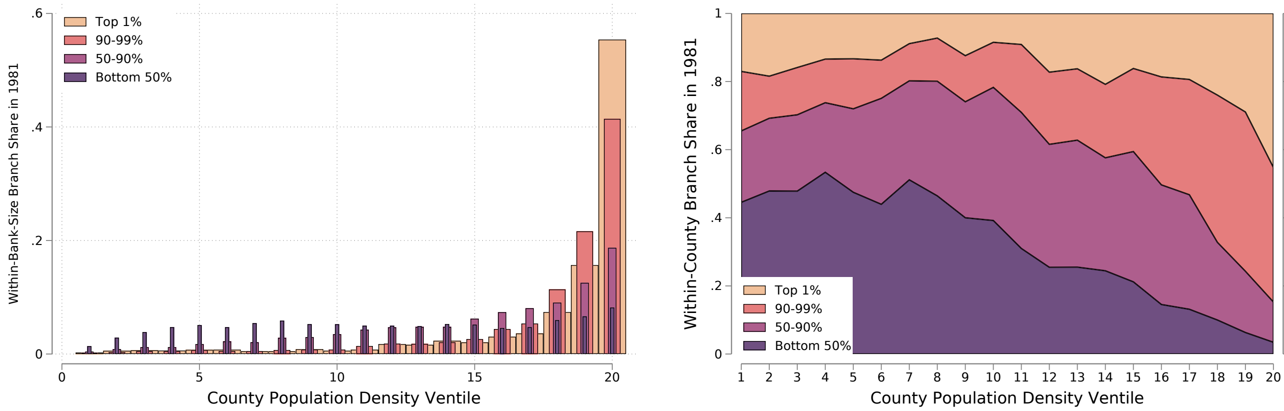
An implication of the dominance of mismatch sorting when these elasticities are sufficiently large is that, all else equal, banks headquartered in locations that are more loan-intensive are more likely to expand to deposit-intensive locations than banks headquartered in deposit-intensive locations. We now turn to contrasting the empirical implications of our model with the evidence on the evolution of the banking industry during its spatial deregulation.

4 Sorting in the Data

4.1 Evidence of Spatial Sorting

We begin our analysis by examining which banks are active across US counties. In Figure 7, we document absolute and relative sorting in 1981, the beginning of our sample. We use local population density as the main local characteristic banks sort on. Relative sorting refers to how banks in one size group sort across space relative to another size group. Absolute sorting refers to how the composition of bank size changes with county density. We group banks into four size bins: the bottom 50%, the 50-90th percentile, the

[37] Another useful example comes at the other extreme. Suppose that a bank can invest separately in the appeal of different types of loans. For example, it could invest in appeal for mortgage loans, commercial loans, trade credit, or others. In such a case, more local demand for one of those types of loans would lead the bank to specialize more in that type of loan, because any changes in wholesale funding would have the same effect on all types of loans. That is, mismatch sorting is a countervailing force to specialization between total loans and total deposits, but it is not a countervailing force to specialization among loan types (or among deposit types).



(a) Relative Sorting in 1981

(b) Absolute Sorting in 1981

Figure 7: This figure plots relative (Panel (a)) and absolute (Panel (b)) sorting patterns in 1981. Panel (a) plots the within-size-bin share of branches across 20 county ventiles by population density. Panel (b) plots the within-density-ventile share of branches across the four size bins. Bank size bins are the bottom 50%, the 50-90th percentile, the 90-99th percentile, and the top 1% of banks by deposits.

90-99th percentile, and the top 1% of banks by total deposits. We further group counties into ventiles based on population density.

Consistent with span-of-control sorting, Panel 7a documents strong relative sorting patterns in 1981. 55% of bank branches belonging to the top 1% of banks are within the densest counties, with the next 30% active in the 16th-19th ventiles. Only 15% of the branches of these banks are in the bottom 3 quartiles of counties by density. Smaller banks are much less concentrated in dense counties. The branch share of the 90-99th percentile of banks in the densest county ventile is 41%, which drops to 18.7% and 8% for the next two size groups, respectively.

We also document absolute sorting patterns in 1981 in Panel 7b. In the least dense counties, 17% of branches belong to the top 1% of banks, while 44.5% belong to the smallest 50% of banks. This is in stark contrast to the most dense counties, where 45% of branches belong to the largest banks and a mere 3% belong to the smallest 50% of banks.

The sorting patterns could potentially be mechanical. If some banks are located in the most dense counties, they are more likely to be large simply due to market size effects. Sorting may therefore have nothing to do with explicit characteristics of banks, and may rather be due to headquarters location choice. We address these concerns by exploiting variation over time created by the geographic deregulation episodes. We focus on relative sorting patterns, though similar results hold for absolute sorting patterns (see Appendix A.5.3). Define the average local population density of bank j in state s in year t to be

$$\log(\text{Density}_{jst}) = \sum_{c \in \mathcal{C}_s} \left(\frac{b_{jct}}{\sum_{c' \in \mathcal{C}_s} b_{jc't}} \right) \log(\text{Density}_{ct}), \tag{16}$$

where Density_{ct} is the population density of county c in year t, $\mathcal{C}_s$ is the set of counties in state s, and b_{jct} is the number of branches of bank j in county c in year t. We focus on sorting patterns within a given state in a given year. Our main regression specification is

$$\log(\text{Density}_{jst}) = \beta \text{Size}_{jt} + \gamma_{st} + \varepsilon_{jst}, \tag{17}$$

where Size_{jt} is measured as log deposits of bank j at time t across all of its bank branches.[38] We interpret a positive β coefficient as evidence of span-of-control sorting, i.e. larger banks are located disproportionately in dense counties. Note that standard heterogeneous firm models, as in Melitz (2003), imply exactly the opposite. In those models, it is the productive firms that sell in the more marginal markets, which would imply a negative β coefficient.

We consider four increasingly restrictive samples for the estimation. First, we estimate (17) for the full sample of banks and states. Second, we use a specification that excludes banks' headquarters counties' density when measuring average local population density to avoid the possibility that sorting is only driven by headquarters location choices. Third, we estimate (17) using only out-of-state banks. This specification allows us to ignore other aspects of the deregulation that may have influenced sorting patterns, such as intra-state banking and branching laws that were also passed in the 1970s and 80s. Finally, in the fourth specification, we interact the state-year fixed effect with a distance bin.[39] This additional restriction addresses concerns that sorting is driven by banks near state lines.

Table I presents the results. We find strong evidence for span-of-control sorting across all specifications. Using the most conservative estimate, a one standard deviation increase in bank size is associated with a 33% increase in the average density of a bank's counties. We use this framework to understand how distance affects this form of sorting. First, we include another specification in Table I that interacts bank size with an indicator, OOS_{js}, for whether they are out-of-state. We also include the indicator in the regression to explore how average density changes with distance. Column (5) in Table I displays the results. Out-of-state banks sort less: the coefficient on the interaction term is negative and economically significant, with out-of-state banks sorting 42% less than in-state banks. However, the coefficient on the out-of-state indicator is positive and significant, implying that on average, they are in relatively dense locations.

Overall, these results show that indeed large banks sort into the densest counties. All banks, large and small, enter more dense locations when they expand out of state. Large banks also sort more into dense locations out of state, but less so than in their headquarters state. This last effect might be the result of distance to their headquarters or the impact of mismatch sorting, as we discuss further below. Remember from Section 2, that large banks use wholesale funding more intensively.

We further explore the role of distance by explicitly interacting bank size with distance bins. We restrict

[38] We can also use total assets of bank j as a measure of size. Given the way that deposits translate into assets in the banking industry, the results are very similar.

[39] We use the following distance bins: 0 (in-state banks), 50 miles, 100 miles, 150 miles, 200 miles, 250 miles, 300 miles, 350 miles, 400 miles, 450 miles, 500 miles, 1000 miles, and 3000 miles.

	Dependent variable: $\log(\text{Density}_{jst})$				
	(1)	(2)	(3)	(4)	(5)
Size_{jt}	0.317^{***}	0.309^{***}	0.182^{***}	0.265^{***}	0.328^{***}
	(0.010)	(0.014)	(0.019)	(0.057)	(0.015)
$\text{Size}_{jt} \times \text{OOS}_{js}$					-0.137^{***}
					(0.021)
OOS_{js}					1.771^{***}
					(0.309)
No Headquarters		✓	✓	✓	✓
Out-of-State Only			✓	✓	
State × Distance Bin FEs				✓	✓
Observations	229,310	82,112	13,349	1,944	98,946
R^2	0.43	0.44	0.59	0.77	0.50
Within R^2	0.06	0.06	0.11	0.08	0.12

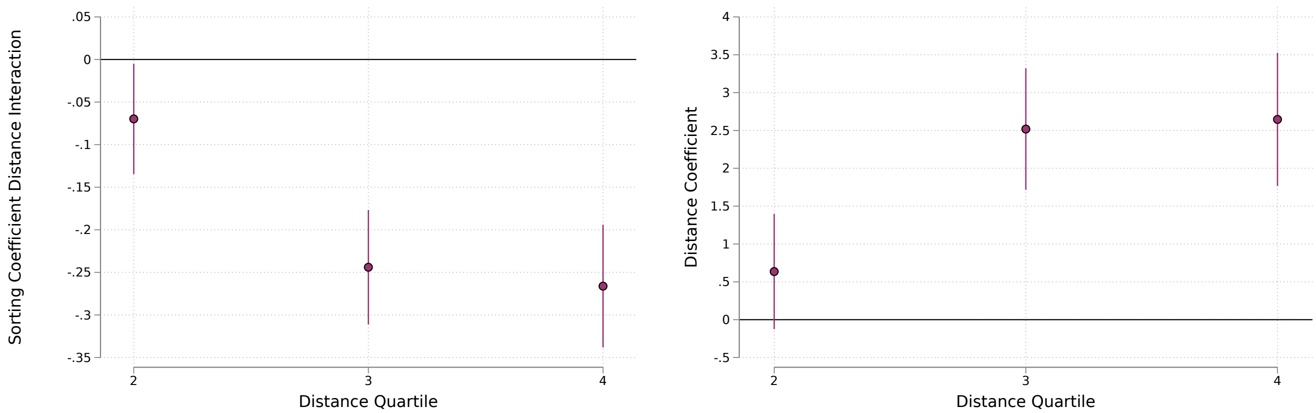
Table I: This table displays regression results for equation (17). The dependent variable is the average log density of firm j's branches at time t in state s. Size_{jt} is the log of bank j's deposits in year t. OOS_{js} is an indicator for whether bank j's headquarters is not in state s. Standard errors are reported in brackets and are two-way clustered at the state and bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the sample to banks that are active in two or more counties to avoid headquarters location biases. Define dist_{js} to be the average distance from bank j's headquarter county to its branches in state s, and let $\text{dist}^q_{js} = \mathbf{1}\{\log(\text{dist}_{js}) \text{ in quartile } q\}$ for $q = 2, 3, 4$. We estimate the regression

$$\log(\text{Density})_{jst} = \beta \text{Size}_{jt} + \sum_{q=2}^{4} \theta_q \text{dist}^q_{js} + \sum_{q=2}^{4} \beta_q \text{Size}_{jt} \times \text{dist}^q_{js} + \gamma_{st} + \varepsilon_{jst}. \tag{18}$$

We report the results graphically in Figure 8. Consistent with the out-of-state regression results, sorting declines with distance, as shown in Figure 8a, though the last two quartiles are not significantly different from each other. Additionally, faraway banks are in more dense counties on average, as shown by the estimated indicator terms in Figure 8b.

We next use a granular geographic approach to understand the determinants of branching in particular counties. For example, do large banks expand into cities relatively more than small banks? Does the distance between a bank and its target county have a measured effect on the number of branches they choose to set



(a) Sorting Interaction Coefficients

(b) Distance Coefficients

Figure 8: This figure displays changes in relative and absolute sorting patterns between 1981 and 2006 for four bank-size bins. Panel (a) shows the change in within-bank-size branch share across density ventiles and Panel (b) shows the change in within-density-ventile branch share across bank size groups. Bank size bins are the bottom 50%, the 50-90th percentile, the 90-99th percentile, and the top 1% of banks by deposits.

up? To answer these questions, we estimate the Poisson regression

$$\log(\mathbb{E}[\text{Branches}_{jct}]) = \underbrace{\delta \text{Size}_{jt} \times \log(\text{Density}_{ct})}_{\text{sorting motives}} + \underbrace{\theta \log(\text{Miles}_{jc})}_{\text{distance effect}} + \gamma_{ct} + \gamma_{jt} + \varepsilon_{jct}. \tag{19}$$

where Branches_{jct} denotes the total number of branches of bank j in county c in year t and Miles_{jc} is the distance in miles from the centroid of bank j's headquarter county and the centroid of county c. We standardize both bank size and log county population density. We interpret a positive δ estimate as evidence for spatial span-of-control sorting: large banks have more branches, but especially so in dense counties.

We limit our sample to banks that at some point in the sample were active in 35 or more counties. We do this for two reasons. First, with over 3,000 counties and 26 years, each bank-year in the data consists of nearly 80,000 observations. With about 9,000 banks per year on average, this gives over 250 million observations, which is too large of a dataset to use with high-dimensional fixed effects. Second, we want to explicitly target banks that are more likely to expand so that we understand exactly what drives these expansion decisions. On average across years, the banks we use in the sample account for 49% of total deposits and 42% of all branches.[40] We further remove banks that change headquarters over the sample period, though this accounts for only a few banks.

We consider three different sub-samples when reporting results. First, we restrict the analysis to out-of-state counties to eliminate the influence of headquarters counties. We then consider only out-of-state bank-county pairs in which a bank did not have any branches in the county at the beginning of the sample.[41]

[40] We experiment with different cutoffs and find similar results.

[41] For this analysis, our sample starts in 1984 because of the availability of brokered deposit data. Some banks had already

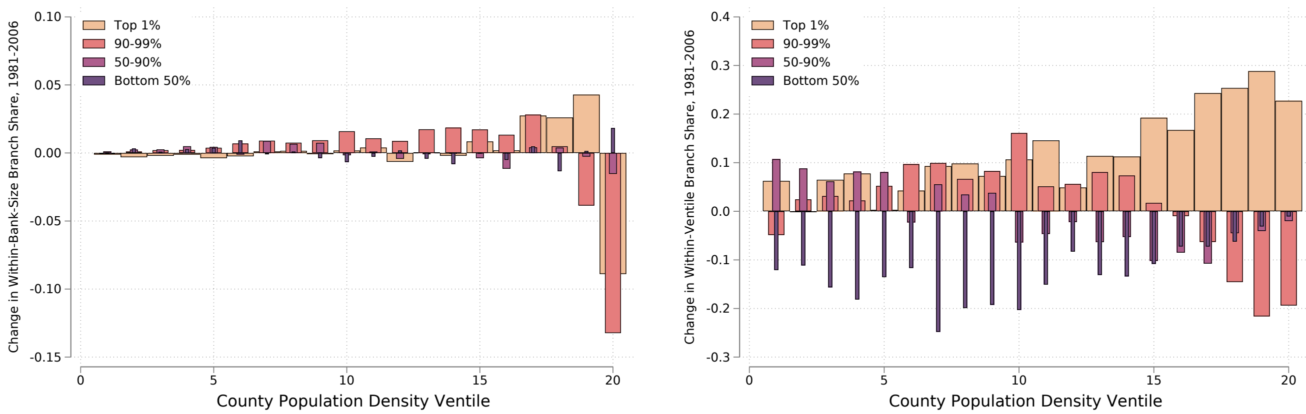
	Dependent variable: Branches_{jct}		
	(1)	(2)	(3)
$\text{Size}_{jt} \times \log(\text{Density}_{ct})$	0.226^{***}	0.251^{***}	0.224^{***}
	(0.012)	(0.010)	(0.011)
$\log(\text{Miles}_{jc})$	-2.002^{***}	-2.002^{***}	-1.785^{***}
	(0.020)	(0.026)	(0.038)
Bank × Year FE	✓	✓	✓
County × Year FE	✓	✓	✓
Out-of-State Counties	✓	✓	✓
No Branches in Initial Year		✓	✓
Balanced Sample			✓
Observations	1,640,677	1,157,586	574,121
Pseudo R^2	0.63	0.63	0.63

Table II: This table displays pseudo-Poisson regression results for equation (19). The dependent variable is the number of branches that bank j has in county c in year t. Size_{jt} is log total deposits of bank j in year t, Density_{ct} is the population density of county c in year t, and Miles_{jc} is the distance in miles between bank j's headquarter county and county c. Size and density are standardized. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, * $p < 0.01$.

Finally, we consider a balanced panel of banks to avoid biases from banks that were either failing or looking to consolidate.

Table II reports the results. We find evidence for spatial span-of-control sorting: δ is positive and statistically significant in all specifications. The magnitudes imply that the average number of branches is 22-25% higher for large banks relative to the average bank for dense counties relative to the average county. In other words, large banks are relatively more active than the average bank in dense counties. We also find evidence that distance discourages branching. The estimates are large: a ten percentage point increase in distance from a bank's headquarters reduces the average number of branches by 17-20%.

begun expanding by then, so we do have some out-of-state branches by 1984.



(a) Change Relative Sorting

(b) Change in Absolute Sorting

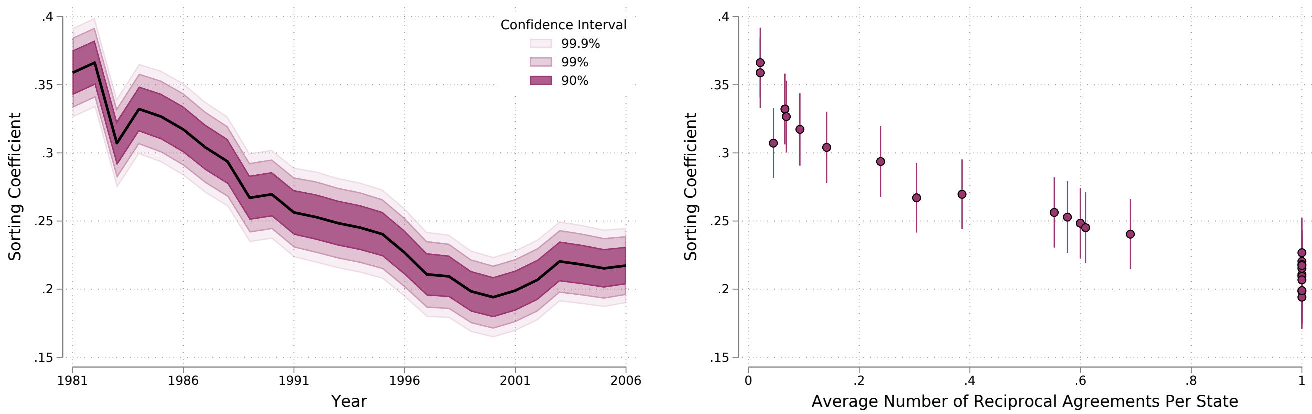
Figure 9: This figure displays changes in relative and absolute sorting patterns between 1981 and 2006 for four bank-size bins. Panel (a) shows the change in within-bank-size branch share across density ventiles, and Panel (b) shows the change in within-density-ventile branch share across bank size groups. Bank size bins are the bottom 50%, the 50-90th percentile, the 90-99th percentile, and the top 1% of banks by deposits.

4.2 Sorting Over Time and the Impact of Deregulation

The rapid spatial deregulation of banks that we documented in Section 2 led to large expansions in the number of branches, particularly those owned by large banks. How did this expansion affect spatial sorting patterns? We start our analysis by studying changes in relative and absolute sorting across the density distribution. Appendix A.5.4 describes our measures of expansion within and across states.

Figure 9 shows how sorting patterns were affected by the expansion of banks across the size distribution. Panel 9a documents changes in relative sorting patterns between 1981 and 2006. The top 1% of banks grew most in the top quartile of counties by density but lost branch share in the most dense counties. We find a similar effect across the size distribution: the 90-99th percentile of banks grew relatively faster in the middle-density counties, and the 50-90th percentile grew the fastest in the bottom half of the county density distribution. The smallest banks *shrunk* the least in the highest-density counties. Panel 9b considers changes in absolute sorting, i.e. changes in within-density-ventile branch shares across the bank size distribution. The top 1% of banks expanded their share in every density ventile, but predominantly in the largest quartile of counties by density. There is a clear fanning out effect: the 90-99th percentiles gained share predominantly in the middle of the density distribution, the 50-90th percentiles gained share in the bottom half of the density distribution, and the smallest 50% lost branch share everywhere but predominantly in the middle and bottom of the density distribution.

The results indicate that large banks expanded, but weakened their sorting by adding branches to dense counties, but not the densest ones where they already had a disproportionate presence. All banks spread out into more types of locations in 2006 which, overall, weakens sorting during this period. We now proceed



(a) Sorting Over Time

(b) Sorting by Average Deregulation

Figure 10: This figure displays the change in relative sorting between 1981 and 2006. Panel (a) plots the estimated sorting coefficients $\{\beta_t\}$ from equation (20). Dark areas display the 90% confidence interval, medium areas display the 99% confidence interval, and light areas display the 99.9% confidence interval. Panel (b) plots the coefficients $\{\beta_t\}$ against the average number of reciprocal agreements across states in year t. Bars represent the 95% confidence interval.

to study this empirical finding in more detail. In particular, we explore how sorting changed over time using our regression analysis. We begin by estimating equation (17) year by year to allow the sorting coefficient to vary over time. Namely, we estimate

$$\log(\text{Density})_{jst} = \beta_t \text{Size}_{jt} + \gamma_{st} + \varepsilon_{jst}, \qquad t = 1981, \ldots, 2006. \tag{20}$$

Figure 10a shows the evolution of the density-size sorting elasticity over time. There is a consistent decline in relative sorting patterns until 1998, after which the sorting estimates plateau. The decline is significant: the coefficient falls from 0.37 in 1981 to an average of 0.22 after 1998.

Figure 10b connects the decline in sorting to geographic deregulation. We plot the estimated sorting coefficient from equations (20) against the average number of reciprocal agreements per state in a given year. There is a clear negative trend: in the early stages of deregulation, sorting estimates are clustered around 0.33. As the deregulation picked up, there is a clear decline, culminating at the 0.22 level following the passage of the IBBEA, when all states deregulated fully.

Motivated by the observed decline in sorting, we consider a more rigorous specification that exploits the staggered changes in inter-state deregulation across states. We also account for the staggered changes in intra-state deregulation, explicitly separating states that allowed organic expansion through branches versus states that only allowed expansion through acquisitions. The regression specification is now

$$\log(\text{Density})_{jst} = \beta_0 \text{Size}_{jt} + \beta_1 \text{Size}_{jt} \times \text{Recip}_{st} + \beta_2 \text{Size}_{jt} \times \text{IntraMA}_{st} + \beta_3 \text{Size}_{jt} \times \text{IntraBr}_{st} + \gamma_{st} + \varepsilon_{jst}, \tag{21}$$

	Dependent variable: log(Density$_{jst}$)			
	(1)	(2)	(3)	(4)
Size$_{jt}$	0.484***	0.480***	0.621***	0.621***
	(0.062)	(0.059)	(0.090)	(0.090)
Size$_{jt}$ × Recip$_{st}$	−0.057**	−0.071**	−0.036	−0.048**
	(0.022)	(0.027)	(0.025)	(0.024)
Size$_{jt}$ × IntraMA$_{st}$	−0.099*	−0.093*	−0.247***	−0.245***
	(0.053)	(0.054)	(0.081)	(0.083)
Size$_{jt}$ × IntraBr$_{st}$	−0.146***	−0.130***	−0.118***	−0.105***
	(0.040)	(0.039)	(0.036)	(0.037)
State × Year FEs	✓	✓	✓	✓
Contiguous Counties		✓		✓
Banks with 2+ Counties			✓	✓
Observations	248,637	248,637	98,544	98,544
R^2	0.44	0.44	0.50	0.50
Within R^2	0.08	0.07	0.12	0.12

Table III: This table displays regression results of equation (21). The dependent variable is the branch-weighted average log density of bank j's branches in year t. Size$_{jt}$ is the log of bank j's total deposits in year t. Recip$_{st}$ is the share of reciprocal agreements involving state s in year t. IntraMA$_{st}$ is in indicator for whether state s allows intra-state branching through acquisitions in year t. IntraBr$_{st}$ is an indicator for whether state s allows intra-state de novo branching in year t. Columns (1) and (3) do not count contiguous county branching deregulation in IntraBr$_{st}$, while Columns (2) and (4) do. Standard errors are reported in parentheses and are two-way clustered at the state and bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

where Recip$_{st}$ is the fraction of states in which state s has a bilateral entry agreement in year t, IntraMA$_{st}$ is an indicator equal to 1 if state s allows intra-state expansion through acquisitions in year t, and IntraBr$_{st}$ is an indicator equal to 1 if state s allows organic intra-state branching throughout the state in year t. Sorting changes, captured by $\{\beta_k\}_{k>0}$, are identified by variation in deregulation across states.

Table III displays the results. Columns (1) and (2) report estimates for the full sample of banks, and Columns (3) and (4) report estimates for banks active in more than one county.[42] Each type of deregulation

[42]Some states only allowed organic branching in counties contiguous to a bank's headquarters county. We include two separate specifications that classify these states as no organic branching and as organic branching. We also consider specifications that limit the sample to banks active in two or more counties to eliminate concerns that headquarters choice affects observed sorting

is associated with a decline in sorting patterns. Intra-state deregulation dominates: in the full sample of banks, intra-state organic branching deregulation reduced the strength of sorting from 0.484 to 0.338, a decline of about 30%, while intra-state acquisition deregulation reduced the strength of sorting further to 0.239, an additional 20% reduction relative to fully regulated states. Inter-state branching also played a role, further reducing sorting by 0.057, or an additional 12% relative to the fully regulated states. Taken together, a fully deregulated state experienced a decline in sorting by around 62%.

The importance of intra-state branching versus acquisitions is reversed for multi-county banks: acquisition deregulation reduced sorting by about 40%, while organic branching reduced sorting by about 17%. Inter-state deregulation remained less important, reducing sorting by about 8% relative to non-deregulated states.

Of course, we cannot rule out that the estimation may be simply picking up pre-trends in sorting patterns. Many states deregulated in-state branching in the late 1970s and early 1980s, which could drive changes in sorting patterns as banks became less geographically constrained within a given state. We therefore further test for causality by looking at the dynamic effects of deregulation on sorting. We estimate an event study specification given by

$$\log(\text{Density}_{jst}) = \beta \text{Size}_{jt} + \sum_{\substack{-5 \leq h \leq 10 \\ h \neq -1}} \beta_h \text{Size}_{jt} \times \text{Open}_{st+h} + \gamma_{st} + \varepsilon_{jst}, \tag{22}$$

where Open_{st+h} is an indicator equal to 1 if $\text{Recip}_{st+h} > 0$. We let $h = 0$ refer to the first period in which a state opened up to any other state. If the results in Table III are driven by changes in sorting induced by intra-state branching deregulation, then the pre-trend coefficients ($h < 0$) should be positive.

Figure 11 plots the results of the event study. The pre-trend coefficients average 0.01 and are all statistically insignificant at the 5% level. All of the post-opening coefficients are negative, and only the initial deregulation year is insignificant. The effects are monotonically declining over time following the initial opening, which likely reflects the increasing degree of openness over time.

In sum, the evidence suggests that geographic deregulation was associated with a weakening pattern of sorting. Sorting was important before and after deregulation, but it was significantly weaker in 2006 than in 1981. Our theory naturally rationalizes these patterns. Span-of-control sorting implies that large banks are located in denser locations. However, because these denser locations demand more loans than deposits, large banks use wholesale funding more intensively, which limits their profitability. The main effect of deregulation, both intra-state and inter-state banking deregulation, is to allow banks to open branches in new locations. Large banks take advantage of this new regulatory environment by opening branches in locations where they face a relatively large demand for deposits. This is exactly mismatch sorting. Large banks expand to locations that reduce their reliance on wholesale funding. Since locations with large deposit intensity are less dense, the result is a reduction in sorting.

patterns.

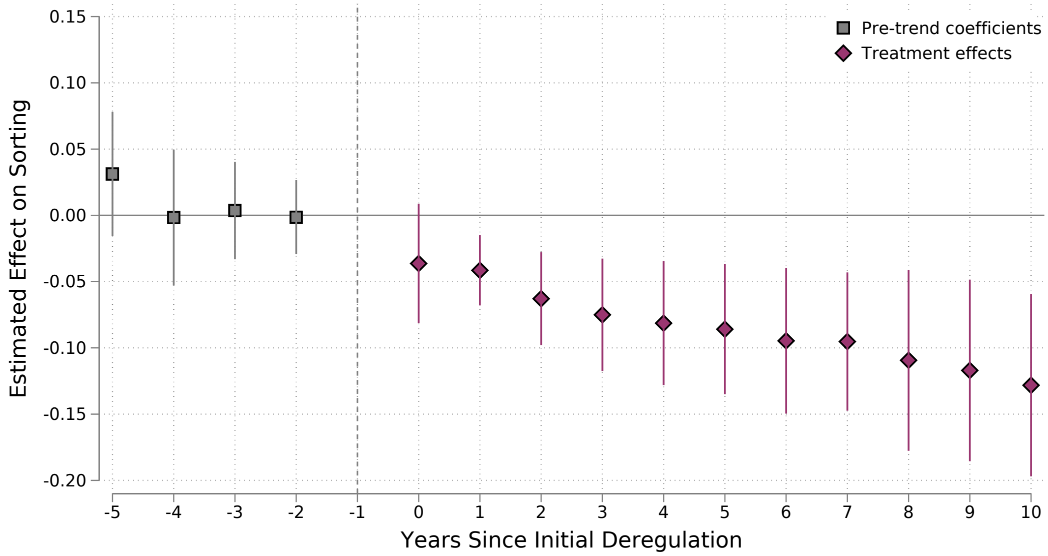


Figure 11: This figure reports the estimated coefficients from the event study (22). Gray squares indicate the pre-trend coefficients and colored diamonds represent the treatment effects. Bars report the 95% confidence interval for each estimate. Standard errors are two-way clustered at the state and bank level.

The above argument requires us to show several important missing pieces of evidence. First, we need to show that denser areas are indeed less deposit-intensive. Second, we need to show that banks in dense locations used more wholesale funding. Third, we need to provide evidence that, as predicted by mismatch sorting, these banks expanded into more deposit-intensive locations and that deregulation made them open branches in these locations even after controlling for other bank characteristics like size and distance to headquarters. Finally, we need to show that large banks' reliance on wholesale funding declined as banks expanded in space. We present this evidence in the next section.

4.3 Connecting Mismatch Sorting and Weakened Sorting Patterns

4.3.1 County Density and Deposit Intensity

We start this section with evidence on the distribution of deposit intensity in space. We collect data on small business loans from the Federal Financial Institutions Examination Council's Community Reinvestment Act (CRA) disclosures. Under the CRA, banks with more than $1 billion in assets are required to disclose all loans to firms with gross revenues of less than $1 million.[43] These loans are reported at the census tract level, which we aggregate up to counties. The data are available starting in 1995.

The spatial mismatch sorting mechanism states that large banks expanded into deposit-abundant regions

[43] While this restriction omits some existing banks, Greenstone et al. (2020) estimate that FFIEC data cover about 86% of the small business loan market.

to gain access to cheap retail deposits, which they could then transfer through their branch network to more profitable lending markets. To understand if this mechanism can lead to the decline in sorting in response to geographic deregulation that we documented above, we need to study how deposit intensity varies with county density. To investigate this pattern we estimate a county-level regression given by

$$\log(D/L)_{ct} = \phi \log(\text{Density}_{ct}) + \text{controls}_{ct} + \gamma_t + \varepsilon_{ct} \tag{23}$$

where $\log(D/L)_{ct}$ denotes the log of the deposits to loans ratio in county c at time t. If $\phi < 0$, then low-density counties have on average more deposits than loans relative to high-density counties, corroborating the pattern required for mismatch sorting to reduce overall sorting in response to geographic deregulation. We progressively include controls in the regression, such as county per-capita income and the number of local banks and branches. We also consider a specification with state-year fixed effects to control for differences in financial development across states and to better connect the results to the sorting regressions in the previous section. Table IV reports the results. In all specifications, we find $\phi < 0$, implying that low-density counties are more deposit-intensive relative to high-density counties.[44]

4.3.2 Headquarter Location and the Use of Wholesale Funding

Having established that denser locations are less deposit intensive, we now study if banks that were headquartered in counties with relatively more loan opportunities used more wholesale funding. To do so, we estimate

$$\text{WFE}_{j,1984} = \beta \log(D/L)_{c_j^{HQ}} + \text{controls}_{j,1984} + \varepsilon_{j,1984}. \tag{24}$$

where $\text{WFE}_{j,1984}$ denotes the log of bank j's wholesale funding exposure in 1984 and $\log(D/L)_{c_j^{HQ}}$ is our measure of deposits to loans for bank j's headquarter county.[45] We gradually add controls for the density of a bank's headquarters county and the size of the bank. We present the results in Table V.

We find that banks use less wholesale funding when they are headquartered in locations that are deposit-intensive. Columns (1) and (4) only consider the relationship between wholesale funding exposure and deposit intensity. In Columns (2) and (5), we add the density of a bank's headquarters county. If dense counties have more banks lending on the interbank market, then wholesale funding may be less costly to obtain, which could drive the results. Further, dense counties may also have more firms or households looking to store longer maturity deposits, which could also increase the propensity for banks to borrow on the wholesale market. Columns (3) and (6) further include the bank's size as a control in the case that large banks have better access to wholesale funds. Consistent with mismatch sorting, even with these controls,

[44]The auto-correlation in our measure of deposit intensity is very high at 0.82 over one year and 0.59 over 10 years, indicating that deposit intensity is a persistent local characteristic. See Appendix A.5.5 for more details.

[45]To calculate a time-invariant measure of deposits to loans at the county level, we take total deposits in a county in 2006 and divide the number of deposits by the total volume of small business loans between 1995 and 2006. The comparison between loan and deposit volume is complicated since deposits are a stock but loans are a flow. We aggregate loans from 1995 through 2006 to better compare the two.

	Dependent variable: log(Deposits$_{ct}$ / Loans$_{ct}$)			
	(1)	(2)	(3)	(4)
Log Population Density	-0.203^{***}	-0.208^{***}	-0.185^{***}	-0.237^{***}
	(0.004)	(0.004)	(0.007)	(0.009)
Log Per-Capita Income		✓	✓	✓
Log # of Banks			✓	✓
Log # of Branches			✓	✓
Year FE	✓	✓	✓	
State × Year FE				✓
Observations	33,884	33,319	33,319	33,319
R^2	0.14	0.15	0.15	0.34
Within R^2	0.10	0.11	0.12	0.10

Table IV: This table displays regression results of equation (23). The dependent variable is the county-level deposit-to-loan ratio in year t. The independent variable of interest is log population density of county c in year t. Column (2) includes county log per-capita income as a control, and columns (3) and (4) add the log number of banks and the log number of branches. Columns (1)-(3) include year fixed effects, while column (4) includes state-year fixed effects. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the coefficient on deposit intensity remains negative and significant.

4.3.3 Spatial Expansion Patterns and the Level of Wholesale Funding

Next, we explore whether banks with more exposure to wholesale funding expanded into locations that were deposit-abundant over this period. To test this, we estimate the Poisson regression

$$\begin{aligned}\log(\mathbb{E}[\text{branches}_{jct}]) =& \beta_0 \text{WFE}_{j,1984} \times \log(D/L)_c + \beta_1 \text{WFE}_{j,1984} \times \log(\text{Density}_{ct}) \\ &+ \phi_0 \text{Size}_{jt} \times \log(D/L)_c + \phi_1 \text{Size}_{jt} \times \log(\text{Density}_{ct}) \\ &+ \delta \log(\text{Dist}_{jc}) + \gamma_{jt} + \gamma_{ct} + \varepsilon_{jct}. \end{aligned} \tag{25}$$

Our coefficient of interest is β_0, which measures the relative propensity of firms with higher levels of wholesale funding to expand into deposit-intensive locations. We include the remaining terms to control for the possibility that expansion decisions are driven by size and density alone. As in previous regressions, we

	Dependent variable: $\text{WFE}_{j,1984}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(D/L)_{c_j^{HQ}}$	-0.073^{***}	-0.040^{**}	-0.041^{**}	-0.070^{**}	-0.026^{*}	-0.034^{**}
	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
$\log(\text{Density})_{c_j^{HQ}}$		0.099^{***}	0.086^{***}		0.141^{***}	0.120^{***}
		(0.007)	(0.008)		(0.007)	(0.007)
Size			0.047^{***}			0.085^{***}
			(0.012)			(0.011)
HQ State FE				✓	✓	✓
Observations	8,570	8,570	8,563	8,570	8,570	8,563
R^2	0.002	0.03	0.03	0.27	0.30	0.31
Within R^2				0.002	0.05	0.06

Table V: This table displays regression results of equation (24). The dependent variable the log of bank j's wholesale funding exposure in 1984. $\log(D/L)_{HQ(j)}$ is the log deposit-to-loan ratio of bank j's headquarter county. Density is the population density of bank j's headquarter county in 1984. Size is the log of bank j's total deposits in 1984. Columns (4)-(6) include headquarters state fixed effects. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

restrict the sample to banks that at some point in the sample are active in 35 or more counties. We further restrict the counties to out-of-state counties in which a bank's headquarters state has a reciprocal agreement. The estimates are reported in Table VI.

We find $\beta_0 > 0$, indicating that banks with higher levels of wholesale funding were relatively likely to expand into deposit-intensive counties after deregulation. The statistical significance and sign of β_0 remain intact when including size interactions in the regression.

To complement this evidence, we explore how wholesale funding exposure prior to deregulation affected the expansion and sorting decisions on banks along the deposits-to-loans (D/L) margin. To do so, we estimate the regression

$$\log{(D/L)}_{jst} = \beta_0 \text{Size}_{jt} + \beta_1 \text{Size}_{jt} \times \text{Recip}_{st} + \beta_2 \text{WFE}_{j,1984} + \beta_3 \text{WFE}_{j,1984} \times \text{Recip}_{st} + \gamma_{st} + \varepsilon_{jst} \quad (26)$$

where $\log{(D/L)}_{jst}$ denotes the branch-weighted average of county-level deposit-to-loan ratios for each bank in each year.

Table VII presents the results. The table reports results for both average log density, columns (1)-(3),

	Dependent variable: branches_{jct}	
	(1)	(2)
$\text{WFE}_{j,1984} \times \log(D/L)_c$	0.294^{***}	0.206^{***}
	(0.026)	(0.031)
$\text{WFE}_{j,1984} \times \log(\text{Density}_{ct})$	0.162^{***}	0.105^{***}
	(0.007)	(0.009)
$\text{Size}_{jt} \times \log(D/L)_c$		0.098^{***}
		(0.016)
$\text{Size}_{jt} \times \log(\text{Density}_{ct})$		0.066^{***}
		(0.005)
$\log(\text{Dist}_{jc})$	-1.8746^{***}	-1.862^{***}
	(0.028)	(0.027)
Bank-Year FE	✓	✓
County-Year FE	✓	✓
Observations	796,328	796,328
Pseudo R^2	0.64	0.64

Table VI: This table displays regression results of equation (25). The dependent variable is the number of bank j's branches in county c in year t. $\text{WFE}_{j,1984}$ is the log of bank j's wholesale funding exposure in 1984. $\log(D/L)_c$ is the deposit-to-loan ratio of county c. Density_{ct} is the population density of county c in year t. $Size_{jt}$ is the log of bank j's total deposits in year t. $\log(\text{Dist}_{jc})$ is the log distance in miles between bank j's headquarter county and county c. All specifications include bank-year and county-year fixed effects. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

and average log deposit-to-loan ratio, columns (4)-(6), as dependent variables. In columns (1) and (4), we exclude the wholesale funding exposure terms to provide a benchmark. We find that, again, large banks are more present in dense counties prior to deregulation (span of control sorting), as well as more present generally in loan-intensive counties (mismatch sorting). Deregulation weakened span-of-control sorting.

Columns (2) and (5) include the log of a bank's wholesale funding exposure in 1984, the earliest year we have data. We find evidence of sorting between wholesale funding exposure and local density: prior to deregulation, banks with higher prior exposure to wholesale funding were disproportionately present in high-density counties. Deregulation led to a decline in the relationship between wholesale funding and average density. Further, the inclusion of wholesale funding weakens the effect of deregulation on size, reducing the

	Dependent variable:					
	$\log(\text{Density})_{jst}$			$\log(D/L)_{jst}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Size_{jt}	0.333***	0.340***	0.348***	−0.041***	−0.035***	−0.035**
	(0.041)	(0.043)	(0.043)	(0.014)	(0.013)	(0.014)
$\text{Size}_{jt} \times \text{Recip}_{st}$	−0.126***	−0.063*	−0.071**	0.000	−0.013	−0.009
	(0.026)	(0.031)	(0.030)	(0.009)	(0.010)	(0.010)
$\text{WFE}_{j,1984}$		0.219***	0.418***		−0.040**	−0.076***
		(0.041)	(0.071)		(0.008)	(0.026)
$\text{WFE}_{j,1984} \times \text{Recip}_{st}$		−0.100***	−0.114**		0.045***	0.057***
		(0.033)	(0.049)		(0.008)	(0.016)
State × Year FE	✓	✓	✓	✓	✓	✓
WFE Median			✓			✓
Observations	249,039	171,203	178,525	248,983	171,162	178,484
R^2	0.44	0.45	0.46	0.22	0.21	0.21
Within R^2	0.07	0.14	0.14	0.01	0.01	0.01

Table VII: This table displays regression results of equation (26). The dependent variable is either the branch-weighted average log density (Columns (1)-(3)) or D/L (Columns (4)-(6)) of bank j's branches in year t. Size_{jt} is the log of bank j's total deposits in year t. $\text{WFE}_{j,1984}$ is the log of bank j's wholesale funding exposure in 1984. Recip_{st} is the share of reciprocal agreements involving state s in year t. Columns (3) and (6) use an indicator specification that assigns bank j to above or below median wholesale funding exposure in 1984. Standard errors are reported in parentheses and are two-way clustered at the state and bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

coefficient by half. This indicates that wholesale funding exposure is an important determinant of both the initial and post-deregulation sorting patterns.

Turning to column (5), we find evidence for mismatch sorting prior to deregulation. Banks with high exposure to wholesale funding were disproportionately active in loan-intensive locations, consistent with the theory. However, deregulation effectively eliminated this form of sorting. This indicates that geographic regulation prevented banks from optimally balancing their loan and deposit businesses, as our theory of mismatch sorting suggests.

For robustness, Columns (3) and (6) use a discrete cutoff for wholesale funding exposure, separating banks into below and above median wholesale funding exposure groups in 1984. The results are qualitatively similar to using the log of wholesale funding exposure.

4.3.4 The Overall Impact of Deregulation on Bank Expansion and Wholesale Funding

We have already shown that banks that started with wholesale funding expanded into less dense locations that were more deposit abundant. The final step is to explore what was the effect of this expansion on the dynamics of a bank's overall reliance on wholesale funding after the deregulation shock. We do this by studying the dynamics of the deregulation shock on a bank's geographic expansion and wholesale funding reliance as a function of the bank's initial size and wholesale funding use. Let Large_j be an indicator equal to 1 if bank j is in the top 5% of banks by deposits in the first sample year, 1984. Given an outcome variable Y_{jt}, we estimate

$$Y_{jt+h} - Y_{jt} = \underbrace{\beta_{0h}\text{Recip}_{jt}}_{\substack{\text{baseline}\\\text{effect}}} + \underbrace{\beta_{1h}\text{Recip}_{jt} \times \text{WFE}_{jt}}_{\substack{\text{additional effect}\\\text{of wholesale funding}}} + \underbrace{\beta_{2h}\text{Recip}_{jt} \times \text{Large}_j}_{\substack{\text{additional}\\\text{size effect}}} + \underbrace{\beta_{3h}\text{Recip}_{jt} \times \text{WFE}_{jt} \times \text{Large}_j}_{\substack{\text{additional size effect}\\\text{of wholesale funding}}}$$
$$+ \beta_{4h}\text{WFE}_{jt} + \beta_{5h}\text{WFE}_{jt} \times \text{Large}_j + \gamma_t + \gamma_j + \varepsilon_{jt} \quad (27)$$

for $h = 1, \ldots, 7$.[46] We consider the relative effect of differential use of wholesale funding, WFE_{jt} and $\text{WFE}_{j't}$, for two banks with identical expansion options, $\text{Recip}_{jt} = \text{Recip}_{j't}$, in an identical size bin, $\text{Large}_j = \text{Large}_{j'}$. The differential effect on outcome $Y_{(\cdot)}$ at horizon h of total deregulation, $\text{Recip}_{jt} = 1$, is then given by $[\beta_{1h} + \beta_{3h}\text{Large}_j](\text{WFE}_{jt} - \text{WFE}_{j't})$. We consider three dependent variables: wholesale funding exposure, total branches, and total counties with at least one branch. We plot the effects for each measure given a one standard deviation increase in wholesale funding for small (below top 5% in deposits) and large (above top 5% in deposits) banks. The standard deviations of wholesale funding are 0.099 and 0.149, respectively. We scale the effects by the mean of outcome Y across years in the sample for each size group for ease of comparison across size groups. The estimates can therefore be interpreted as the additional deregulation effect of wholesale funding on the percentage growth in the outcome variable.[47]

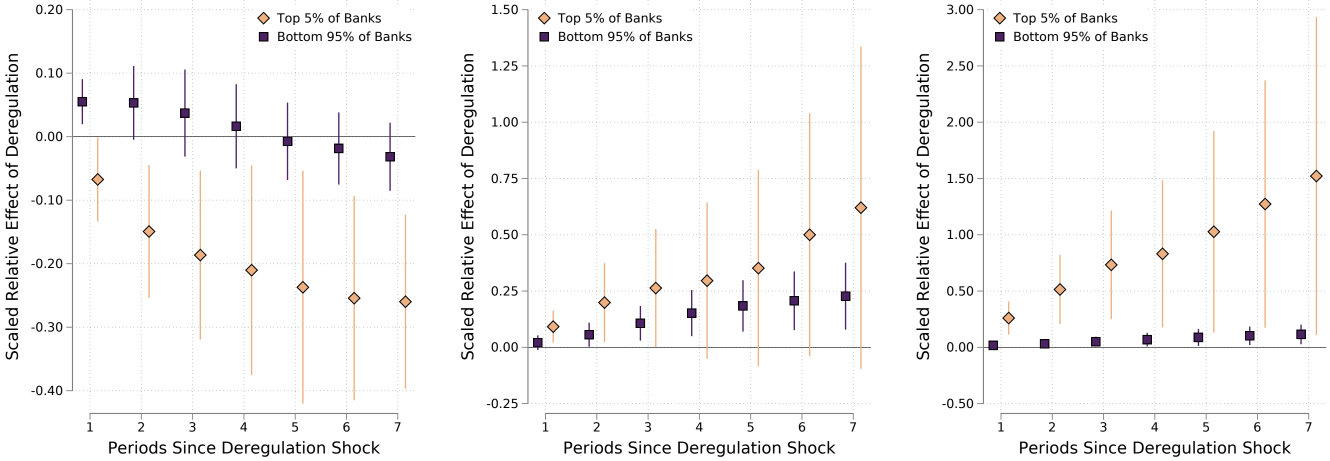
Figure 12 plots the results.[48] Panel 12a shows the effects on wholesale funding exposure. Small firms mildly increase wholesale funding immediately after deregulation, but the effect is small and it reverts to zero by the fourth year after deregulation. However, large firms strongly decrease their wholesale funding exposure immediately after deregulation. The effect grows over time and stabilizes at a 25% decline relative to the effect on banks with average exposure six years after the shock.

Hence, large banks that use large amounts of wholesale funding reduce their reliance on wholesale funding in response to deregulation, exactly the prediction of mismatch sorting. They do so by expanding

[46] We also run this regression in levels and find similar results.

[47] We choose not to use logs due to the large number of near zeros in the number of branches or counties.

[48] Estimated coefficients are presented in Appendix A.5.6.



(a) Wholesale Funding Exposure

(b) Bank Branches

(c) Number of Active Counties

Figure 12: Local projection estimates for the effect of wholesale funding on bank expansion after deregulation. Effects are for a one standard deviation increase in wholesale funding scaled by the mean of the outcome variable. Panel (a) displays the effects on wholesale funding exposure, Panel (b) displays the effects on bank branches, and Panel (c) displays the effects on the number of counties with at least one branch. Square purple markers show estimates for the bottom 95% of banks by deposits, and tan diamond markers show estimates for the top 5% of banks by deposits. Bars around estimates represent the 95% confidence interval. Standard errors are clustered at the bank headquarters state level.

geographically as the other two panels in Figure 12 indicate. For both branches and the number of active counties, panels (12b) and (12c) exhibit positive and increasing cumulative effects of wholesale funding on growth following a deregulation shock. The estimates for branches are relatively noisy, with only the first three period effects significant at the 5% level for large firms, while the estimates for the number of counties are significant at the 5% level for all periods. Large firms experience a larger relative effect than small firms for both variables, though again, the estimates for branches are more noisy and not always statistically significant across groups. It is worth noting the magnitude of the effects for the number of active counties. We estimate that, seven years after the deregulation shock, a large bank with a one standard deviation higher level of wholesale funding increased its number of active counties by more than 150% relative to the average large bank. The estimates are much smaller for small banks (10%).[49]

Taken together, this section showed that geographic deregulation relaxed liquidity constraints for banks, allowing them to raise deposits through branching and reduce their exposure to relatively expensive wholesale funding. Following deregulation, large banks with high wholesale funding reliance expanded significantly relative to average banks, both in terms of branches and counties. Deregulation also led to a decline in

[49]That the estimates for branches are not as significant or large for large banks is not necessarily surprising. Many banks could expand into a new county and open a single branch, implying a small increase in the number of branches, but a relatively large increase in their number of active counties.

the use of wholesale funds in these banks relative to other large banks with average use of wholesale funds. Through the lens of our model, these effects are well accounted for by mismatch sorting. Deregulation allowed banks to expand geographically, and large banks that used wholesale funds more intensively –due to their presence in more dense locations (span-of-control sorting)– expanded to less dense locations where deposit intensity was larger (as we showed above). This in turn decreased overall sorting over time, as we also documented. The impact of deregulation on the spatial distribution of the banking industry is, therefore, the result of a balance between the two forms of sorting uncovered by our theory, and the scale economies that allowed top banks to expand to take advantage of the new opportunities that resulted from deregulation.

5 Conclusion

The spatial deregulation of the U.S. banking industry since the 1980s provides perhaps the most salient evidence of the spatial sorting of banks in space. We have documented that the starting point was an industry in which top banks had headquarters in dense counties with an abundance of investment opportunities but relatively few deposits. This made them large, but also reliant on expensive wholesale funding that limited their profitability. The initial allocation of banks exhibited sorting: denser more expensive locations had a larger presence of large banks, while less dense locations had a larger presence of small banks.

In Oberfield et al. (2024) we provide a theory that rationalizes this initial form of sorting for industries with multi-plant firms. It shows that a model in which the cost of reaching consumers depends on their distance to the firm's closest plant, firms face fixed costs for setting up additional branches, and firms face span-of-control costs that make managing more plants costly in terms of firm productivity, generated this for of span-of-control sorting. We also showed that this was a clear pattern in the data for most industries with multi-plant firms.

The same mechanisms can explain the initial allocation of banks across locations. However, the banking industry has specific features that are essential to explaining the evidence for the deregulation episode. In particular, banks collect deposits and extend loans across heterogeneous locations, and the balance of loans to deposit needs to be financed with relatively expensive wholesale funds. Hence, an important part of the spatial branch location problem of banks is to match total deposits and loans. This leads to an additional force for sorting in space that we have labeled "mismatch sorting". This form of sorting makes banks open branches in locations that are relatively abundant in deposits if they currently rely heavily on wholesale funds, and in loan-abundant locations if they do not. We provide a spatial theory of bank competition in space in which these two forms of sorting operate simultaneously.

The evidence of the deregulation period is well accounted for by the balance between these two forms of sorting. Large banks with headquarters in large urban areas that used wholesale funding extensively expanded into smaller locations, thereby reducing their reliance on wholesale funding. By doing so they displaced small banks that either exited or moved to denser locations. The ability to tap into the abundance of deposits in smaller, less dense, locations allowed top banks to grow and make fixed-cost investments in customer appeal that increase their profitability. The result is a large geographic expansion of top banks into smaller locations and a reduction in overall sorting. Ultimately, these spatial patterns implied access for consumers in small urban and rural areas to the technology and branch network of the top U.S. banks. Furthermore, according to our theory, banks had no incentive to price discriminate against these new customers.

Our theory of the spatial competition and expansion of banks abstracts from some potentially important forces. First, we abstract from risk management and diversification motives. The spatial expansion of banks could be, at least in part, related to the objective of diversifying the deposit and loan portfolios of banks across industries and locations. Second, we do not micro-found the reasons why deposits are relatively cheap but wholesale funding is relatively expensive, and increasingly so as banks use more of it. This could be the result of government policies, like deposit insurance, but also the risk profile of large versus small banks, a form of heterogeneity that we abstract from. In addition to abstracting from these forces, we also do not provide an evaluation of the welfare impact of the spatial deregulation of the banking industry in the U.S. Nor do we measure the importance of the spatial expansion of banks in generating these welfare gains. The spatial banking framework we propose in this paper can certainly be used to do so in future work.

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A Appendix

A.1 Household Problem

Household i's demand for deposits and demand for loans depends on the respective interest rates. We assume household i's demand for deposits takes the form $\mathfrak{d}_i \tilde{\mathcal{D}}\left(r^D\right)$, while its demand for loans takes the form $\mathfrak{l}_i \tilde{\mathcal{L}}\left(r^L\right)$. Each household has a particular taste for each bank. Household i's taste for bank j has components that are common to all households in location ℓ, $\tilde{Q}^D_{j\ell}$ and $\tilde{Q}^L_{j\ell}$, as well as idiosyncratic components, $\varepsilon^D_{ij}, \varepsilon^L_{ij}$.

Household i in location ℓ chooses bank j and bank branch $o \in O_j$ for deposits and for loans that maximizes its indirect utility

$$
\begin{gathered}
\max_{j,o\in O_j} G^D\left(r^D_{jo}\right) - \tilde{T}^D\left(\delta_{\ell o}\right) + \tilde{Q}^D_{j\ell} + \eta\varepsilon^D_{ij} \\
\max_{j,o\in O_j} G^L\left(r^L_{jo}\right) - \tilde{T}^L\left(\delta_{\ell o}\right) + \tilde{Q}^L_{j\ell} + \eta\varepsilon^L_{ij}
\end{gathered}
$$

We assume that the vectors $\left\{\varepsilon^D_{ij}\right\}_j$ and $\left\{\varepsilon^D_{ij}\right\}_j$ are drawn from a standard Gumbel distribution, are independent across j, but may be correlated across uses (e.g., we allow for the possibility that $\varepsilon^D_{ij} = \varepsilon^L_{ij}$ for each j). For households in ℓ, let $o^D_{j\ell}$ and $o^L_{j\ell}$ be the branches the household would use if it chose to use bank j for deposits and for loans.

The probability of choosing bank j or deposits is

$$
\begin{aligned}
\Pr\left(\text{household } i \text{ chooses bank } j \text{ for deposits}\right) &= \frac{e^{\eta\left[G^D\left(r^D_{jo^D_{j\ell}}\right)+\tilde{Q}^D_{j\ell}-\tilde{T}^D\left(\delta_{\ell o^D_{j\ell}}\right)\right]}}{P^D_\ell} \\
\Pr\left(\text{household } i \text{ chooses bank } j \text{ for loans}\right) &= \frac{e^{\eta\left[G^L\left(r^L_{jo^L_{j\ell}}\right)+\tilde{Q}^L_{j\ell}-\tilde{T}^L\left(\delta_{\ell o^L_{j\ell}}\right)\right]}}{P^L_\ell}
\end{aligned}
$$

where the terms in the denominators are

$$
\begin{aligned}
P^D_\ell &\equiv \sum_j e^{\eta\left[G^D\left(r^D_{jo^D_{j\ell}}\right)+\tilde{Q}^D_{j\ell}-\tilde{T}^D\left(\delta_{\ell o^D_{j\ell}}\right)\right]} \\
P^L_\ell &\equiv \sum_j e^{\eta\left[G^D\left(r^L_{jo^L_{j\ell}}\right)+\tilde{Q}^L_{j\ell}-\tilde{T}^L\left(\delta_{\ell o^L_{j\ell}}\right)\right]}
\end{aligned}
$$

For bank j, local deposits and local demand will be

$$
\begin{aligned}
D_{j\ell} &= \frac{e^{\eta\left[G^D\left(r^D_{jo^D_{j\ell}}\right)+\tilde{Q}^D_{j\ell}-\tilde{T}^D\left(\delta_{\ell o^D_{j\ell}}\right)\right]}}{P^D_\ell}\int_{i\in I_\ell}\mathfrak{d}_i\tilde{\mathcal{D}}\left(r^D_{j,o^D_{j\ell}}\right)di \\
L_{j\ell} &= \frac{e^{\eta\left[G^L\left(r^L_{jo^L_{j\ell}}\right)+\tilde{Q}^L_{j\ell}-\tilde{T}^L\left(\delta_{jo^L_{j\ell}}\right)\right]}}{P^L_\ell}\int_{i\in I_\ell}\mathfrak{l}_i\tilde{\mathcal{L}}\left(r^L_{j,o^L_{j\ell}}\right)di
\end{aligned}
$$

Define the following objects:

$$
\begin{aligned}
A^D_\ell &\equiv \frac{1}{P^D_\ell}\int_{i\in I_\ell}\mathfrak{d}_i di \\
A^L_\ell &\equiv \frac{1}{P^L_\ell}\int_{i\in I_\ell}\mathfrak{l}_i di \\
\mathcal{D}(r) &\equiv e^{\eta G^D(r)}\tilde{\mathcal{D}}(r) \\
\mathcal{L}(r) &\equiv e^{\eta G^L(r)}\tilde{\mathcal{L}}(r) \\
Q^D_{j\ell} &\equiv e^{\eta\tilde{Q}^D_{j\ell}} \\
Q^L_{j\ell} &\equiv e^{\eta\tilde{Q}^L_{j\ell}} \\
T^D(\delta) &= e^{-\eta\tilde{T}^D(\delta)} \\
T^L(\delta) &= e^{-\eta\tilde{T}^L(\delta)}
\end{aligned}
$$

Then bank j's local deposits and local loan demand will be

$$
\begin{aligned}
D_{j\ell} &= T^D\left(\delta_{o^D_{j\ell},\ell}\right)Q^D_{j\ell}A^D_\ell\mathcal{D}\left(r^D_{j,o^D_{j\ell}}\right) \\
L_{j\ell} &= T^L\left(\delta_{o^L_{j\ell},\ell}\right)Q^L_{j\ell}A^L_\ell\mathcal{L}\left(r^D_{j,o^L_{j\ell}}\right)
\end{aligned}
$$

A.2 Proofs

A.2.1 Proof of Lemma 1

Proof. We give here an argument for deposit rates. The argument for lending rates is virtually identical. Consider a relaxed problem in which each bank can choose a separate price for consumers in every location, and also choose which branch consumers in each location use. Then bank j's relaxed problem would be

$$\pi_j = \sup_{\substack{W_j, D_j, L_j, O_j, \bar{Q}_j^D, \bar{Q}_j^L, \\ \{D_{j\ell}, L_{j\ell}, r_{j\ell}^D, r_{j\ell}^L o_{j\ell}^D, o_{j\ell}^L\}_\ell}} \int \left[\left(r_{j\ell}^L - \theta_j^L\right) L_{j\ell} - \left(r_{j\ell}^D + \theta_j^D\right) D_{j\ell}\right] d\ell - R\left(\frac{W_j}{D_j}\right) W_j - \sum_{o \in O_j} \Psi_o - w_j^* H(|O_j|) - w_j^* C(\bar{Q}_j^D, \bar{Q}_j^L$$

subject to

$$D_{j\ell} = T^D\left(\delta_{o_{j\ell}^D, \ell}\right) Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_{j\ell}^D\right) \tag{28}$$

$$L_{j\ell} = T^L\left(\delta_{o_{j\ell}^L, \ell}\right) Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_{j\ell}^L\right) \tag{29}$$

as well as (4), (5), (6), (7), and $W_j = D_j - L_j$. Let μ_j^D be the multiplier on (6). Eliminating $D_{j\ell}$ by substituting in the constraint $D_{j\ell} = T^D\left(\delta_{o_{j\ell}^D, \ell}\right) Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_{j\ell}^D\right)$, the Lagrangian can be rearranged so that $r_{j\ell}^D, o_{j\ell}^D$ satisfy

$$\max_{r_{j\ell}^D, o_{j\ell}^D} \left(\mu_j^D - r_{j\ell}^D - \theta_j^D\right) T^D\left(\delta_{o_{j\ell}^D, \ell}\right) Q_{j\ell} A_\ell^D \mathcal{D}\left(r_{j\ell}^D\right)$$

Thus the solution to this relaxed problem is $r_{j\ell}^D = \arg\max_r \left(\mu_j^D - r - \theta_j^D\right) \mathcal{D}(r)$ and $o_{j\ell}^D = \arg\max_{o \in O_j} T^D\left(\delta_{o\ell}\right) = \arg\min_{o \in O_j} \delta_{o\ell}$. Now note that it is feasible for the bank to implement this allocation in the original problem if it sets $r_{jo}^D \equiv \arg\max_r \left(\mu_j^D - r - \theta_j^D\right) \mathcal{D}(r)$. Since the household faces the same deposit rate at each branch, they will simply choose the closest branch. ■

A.2.2 Proof of Lemma 3

Proof. Toward a contradiction, suppose that $\sigma_2/z_2^D \leq \sigma_1/z_1^D$. Then this will imply that bank 2 places weakly more branches than bank 1 at each location. To see this, note that the FOC for bank 2's branches at location ℓ implies that either $n_{1\ell} = 0$, in which case $n_{2\ell} \geq n_{1\ell}$, or $n_{1\ell} > 0$, in which case

$$J_{2\ell}^D A_\ell^D \kappa^{D\prime}(n_{2\ell}) + \frac{z_2^L}{z_2^D} J_{2\ell}^L A_\ell^L \kappa^{L\prime}(n_{2\ell}) \leq \frac{\psi_\ell + \sigma_2}{z_2^D \phi_{2\ell}} \leq \frac{\psi_\ell + \sigma_1}{z_1^D \phi_{1\ell}} = J_{1\ell}^D A_\ell^D \kappa^{D\prime}(n_{1\ell}) + \frac{z_1^L}{z_1^D} J_{1\ell}^L A_\ell^L \kappa^{L\prime}(n_{1\ell})$$

Since $\kappa^{D\prime}$ and $\kappa^{L\prime}$ are both decreasing, this inequality can only hold if $n_{2\ell} > n_{1\ell}$. Thus either $\int n_{2\ell} d\ell = \int n_{1\ell} d\ell = 0$, or $\int n_{2\ell} d\ell > \int n_{1\ell} d\ell$, a contradiction. ■

Proof. Toward a contradiction, suppose that $\sigma_2 \leq \sigma_1$. Then this will imply that bank 2 places weakly more branches than bank 1 at each location. To see this, note that the FOC for bank 2's branches at location ℓ implies that either $n_{1\ell} = 0$, in which case $n_{2\ell} \geq n_{1\ell}$, or $n_{1\ell} > 0$, in which case

$$J_{2\ell}^D A_\ell^D \kappa^{D\prime}(n_{2\ell}) + \frac{z_2^L}{z_2^D} J_{2\ell}^L A_\ell^L \kappa^{L\prime}(n_{2\ell}) \leq \frac{\psi_\ell + \sigma_2}{z_2^D \phi_{2\ell}} < \frac{\psi_\ell + \sigma_1}{z_1^D \phi_{1\ell}} = J_{1\ell}^D A_\ell^D \kappa^{D\prime}(n_{1\ell}) + \frac{z_1^L}{z_1^D} J_{1\ell}^L A_\ell^L \kappa^{L\prime}(n_{1\ell}) \tag{30}$$

Since $\kappa^{D\prime}$ and $\kappa^{L\prime}$ are both decreasing, this inequality can only hold if $n_{2\ell} > n_{1\ell}$. Thus either $\int n_{2\ell} d\ell = \int n_{1\ell} d\ell = 0$, or $\int n_{2\ell} d\ell > \int n_{1\ell} d\ell$, a contradiction.

Now, suppose Assumption 1 holds. Let b denote the upper bound on the elasticities of $\kappa^{D\prime}$ and $\kappa^{L\prime}$, so that

$$\sup_{u \in \{D,L\}, n \geq 0} \frac{-n\kappa^{u\prime\prime}(n)}{\kappa^{u\prime}(n)} \leq b \leq \inf_{N \geq 0} \frac{Nh''(N)}{h'(N)}.$$

Let $\zeta \equiv \frac{z_2^D}{z_1^D} = \frac{z_2^L}{z_1^L} > 1$. Toward a contradiction, suppose that $\sigma_2/z_2^D \leq \sigma_1/z_1^D$, or that $\sigma_2 \leq \zeta\sigma_1$.

We will show that this implies that $n_{2\ell} \geq \zeta^{1/b} n_{1\ell}$ for each location. This clearly holds for $n_{1\ell} = 0$. If $n_{1\ell} > 0$, then (30) implies that

$$\zeta < \zeta \frac{z_1^D J_{1\ell}^D A_\ell^D \kappa^{D\prime}(n_{1\ell}) + z_1^L J_{1\ell}^L A_\ell^L \kappa^{L\prime}(n_{1\ell})}{z_2^D J_{2\ell}^D A_\ell^D \kappa^{D\prime}(n_{2\ell}) + z_2^L J_{2\ell}^L A_\ell^L \kappa^{L\prime}(n_{2\ell})} = \frac{\beta_\ell \kappa^{D\prime}(n_{1\ell}) + \kappa^{L\prime}(n_{1\ell})}{\beta_\ell \kappa^{D\prime}(n_{2\ell}) + \kappa^{L\prime}(n_{2\ell})}$$

where $\beta_\ell \equiv \frac{z_2^D J_{2\ell}^D A_\ell^D}{z_2^L J_{2\ell}^L A_\ell^L} = \frac{z_1^D J_{1\ell}^D A_\ell^D}{z_1^L J_{1\ell}^L A_\ell^L}$. Taking logs and using the fundamental theorem of calculus and the definition of b gives

$$\begin{aligned}
\log\zeta &< -\int_{\log n_{1\ell}}^{\log n_{2\ell}} \frac{\beta_\ell \kappa^{D\prime\prime}(e^u) + \kappa^{L\prime\prime}(e^u)}{\beta_\ell \kappa^{D\prime}(e^u) + \kappa^{L\prime}(e^u)} e^u du \\
&\leq \int_{\log n_{1\ell}}^{\log n_{2\ell}} \frac{\beta_\ell \kappa^{D\prime}(e^u) b + \kappa^{L\prime}(e^u) b}{\beta_\ell \kappa^{D\prime}(e^u) + \kappa^{L\prime}(e^u)} du \\
&= b\left(\log n_{2\ell} - \log n_{1\ell}\right)
\end{aligned}$$

Together, these imply either $N_2 = N_1 = 0$ or $N_2 > \zeta^{1/b} N_1$. If $N_2 > 0$, we can derive the contradiction:

$$\begin{aligned}
\log(\sigma_2/\sigma_1) &= \log h'(N_2) - \log h'(N_1) = \int_{\log N_1}^{\log N_2} \frac{e^u h''(e^u)}{h'(e^u)} du \geq \int_{\log N_1}^{\log N_2} b dN = b\left(\log N_2 - \log N_1\right) \\
&> b \left(\log \zeta^{1/b}\right) = \log\zeta
\end{aligned}$$

■

A.2.3 Proof of Proposition 4

Proof. The two banks' first-order conditions for a location ℓ can be expressed as

$$\frac{J_{2\ell}^D A_\ell^D z_2^D \kappa^{D\prime}(n_{2\ell}) + J_{2\ell}^L A_\ell^L z_2^L \kappa^{L\prime}(n_{2\ell})}{J_{1\ell}^D A_\ell^D z_1^D \kappa^{D\prime}(n_{1\ell}) + J_{1\ell}^L A_\ell^L z_1^L \kappa^{L\prime}(n_{1\ell})} = \frac{\psi_\ell + \sigma_2}{\psi_\ell + \sigma_1}$$

Letting α be the common value of $\frac{J^D_{j\ell}A^D_\ell}{J^L_{j\ell}A^L_\ell}$ and let $\zeta = \frac{z^D_2}{z^D_1} = \frac{z^L_2}{z^D_1} > 1$, this can be rearranged as

$$\frac{\alpha\kappa^{D\prime}(n_{2\ell}) + \kappa^{L\prime}(n_{2\ell})}{\alpha\kappa^{D\prime}(n_{1\ell}) + \kappa^{L\prime}(n_{1\ell})} = \frac{1}{\zeta}\frac{\psi_\ell + \sigma_2}{\psi_\ell + \sigma_1}$$

Note that since $\sigma_2 > \sigma_1$, the right-hand side is strictly decreasing in ψ_ℓ. Further, the right hand side is continuous in ψ_ℓ, and since $\zeta > 1$, there is a unique $\bar{\psi}$ such that if $\psi_\ell = \bar{\psi}$ then the right hand side is one, and $n_{2\ell} = n_{1\ell}$. If $\psi_\ell > \bar{\psi}$, the RHS is less than one, and since $\alpha\kappa^{D\prime}(\cdot) + \kappa^{L\prime}(\cdot)$ is decreasing, it must be that $n_{2\ell} > n_{1\ell}$. Alternatively, if $\psi_\ell < \bar{\psi}$, the RHS is greater than one and $n_{2\ell} > n_{1\ell}$. ■

A.2.4 Proof of Proposition 5

Proof. First, note that the envelope theorem and the fact that $R(\omega)$ is increasing and convex imply that $\max_r \left[R(\omega) + \omega(1+\omega)R'(\omega) - r - \theta^D\right]\mathcal{D}(r)$ is increasing in ω while $\max_r \left[r - \theta^L - R(\omega) - \omega R'(\omega)\right]\mathcal{L}(r)$ is decreasing in ω. As a result, $\omega_2 > \omega_1$ gives

$$\lambda^D_2\mathcal{D}(r^D_2) > \lambda^D_1\mathcal{D}(r^D_1)$$
$$\lambda^L_2\mathcal{L}(r^L_2) < \lambda^L_1\mathcal{L}(r^L_1)$$

Consider a location in which $Q^D_{2\ell} \geq Q^D_{1\ell}$ is the same and $n_{1\ell} > 0$. Letting $x^D_{j\ell} \equiv Q^D_{j\ell}\lambda^D_j\mathcal{D}(r^D_j)$ and $x^L_{j\ell} \equiv Q^L_{j\ell}\lambda^L_j\mathcal{L}(r^L_j)$, the FOCs imply

$$A^D_\ell x^D_{2\ell}\kappa^{D\prime}(n_{2\ell}) + A^L_\ell x^L_{2\ell}\kappa^{L\prime}(n_{2\ell}) \leq \psi_\ell + \sigma_2 = \psi_\ell + \sigma_1 = A^D_\ell x^D_{1\ell}\kappa^{D\prime}(n_{1\ell}) + A^L_\ell x^L_{1\ell}\kappa^{L\prime}(n_{1\ell})$$

This can be rearranged as

$$x^D_{2\ell}\kappa^{D\prime}(n_{2\ell}) + \frac{1}{\alpha_\ell}x^L_{2\ell}\kappa^{L\prime}(n_{2\ell}) \leq x^D_{1\ell}\kappa^{D\prime}(n_{1\ell}) + \frac{1}{\alpha_\ell}x^L_{1\ell}\kappa^{L\prime}(n_{1\ell})$$

and further as

$$\kappa^{D\prime}(n_{2\ell}) \leq \frac{x^D_{1\ell}}{x^D_{2\ell}}\kappa^{D\prime}(n_{1\ell}) + \frac{1}{\alpha_\ell}\left[\frac{x^L_{1\ell}\kappa^{L\prime}(n_{1\ell}) - x^L_{2\ell}\kappa^{L\prime}(n_{2\ell})}{x^D_{2\ell}}\right]$$

Since $\frac{\lambda^D_1\mathcal{D}(r^D_1)}{\lambda^D_2\mathcal{D}(r^D_2)} < 1$, $\frac{x^D_{1\ell}}{x^D_{2\ell}}$ is bounded above by a number smaller than one. In addition, the term in brackets is bounded. Therefore there exists a $\bar{\alpha}$ such that if $\alpha_\ell > \bar{\alpha}$ then $\kappa^{D\prime}(n_{2\ell}) < \kappa^{D\prime}(n_{1\ell})$, which implies $n_{2\ell} > n_{1\ell}$.

Similarly, consider a location in which $Q^L_{1\ell} \geq Q^L_{2\ell}$ and $n_{2\ell} > 0$. The FOCs imply

$$A^D_\ell x^D_{2\ell}\kappa^{D\prime}(n_{2\ell}) + A^L_\ell x^L_{2\ell}\kappa^{L\prime}(n_{2\ell}) = \psi_\ell + \sigma_2 = \psi_\ell + \sigma_1 \geq A^D_\ell x^D_{1\ell}\kappa^{D\prime}(n_{1\ell}) + A^L_\ell x^L_{1\ell}\kappa^{L\prime}(n_{1\ell})$$

This can be rearranged as

$$\alpha_\ell x_{2\ell}^D \kappa^{D\prime}(n_{2\ell}) + x_{2\ell}^L \kappa^{L\prime}(n_{2\ell}) \geq \alpha_\ell x_{1\ell}^D \kappa^{D\prime}(n_{1\ell}) + x_{1\ell}^L \kappa^{L\prime}(n_{1\ell})$$

or further as

$$\alpha_\ell \left[\frac{x_{2\ell}^D \kappa^{D\prime}(n_{2\ell}) - x_{1\ell}^D \kappa^{D\prime}(n_{1\ell})}{x_{1\ell}^L} \right] + \frac{x_{2\ell}^L}{x_{1\ell}^L} \kappa^{L\prime}(n_{2\ell}) \geq \kappa^{L\prime}(n_{1\ell})$$

Since $\frac{\lambda_2^L \mathcal{L}(r_2^L)}{\lambda_1^L \mathcal{L}(r_1^L)} < 1$, $\frac{x_{2\ell}^L}{x_{1\ell}^L}$ is bounded above by a number smaller than 1. Further, the term in brackets is bounded. Therefore there exists an $\underline{\alpha}$ such that $\alpha_\ell < \underline{\alpha}$ implies $\kappa^{L\prime}(n_{2\ell}) > \kappa^{L\prime}(n_{1\ell})$ and hence $n_{2\ell} < n_{1\ell}$.

Finally, in the case where $\kappa^D(n) = \kappa^L(n) \equiv \kappa(n)$ for all n. If $Q_{1\ell}^D = Q_{2\ell}^D = Q_{1\ell}^L = Q_{2\ell}^L$, the FOCs imply

$$\alpha_\ell \lambda_2^D \mathcal{D}(r_2^D) \kappa'(n_{2\ell}) + \lambda_2^L \mathcal{L}(r_2^L) \kappa'(n_{2\ell}) = \alpha_\ell \lambda_1^D \mathcal{D}(r_1^D) \kappa'(n_{1\ell}) + \lambda_1^L \mathcal{L}(r_1^L) \kappa'(n_{1\ell})$$

This can be rearranged as

$$\frac{\alpha_\ell \lambda_2^D \mathcal{D}(r_2^D) + \lambda_2^L \mathcal{L}(r_2^L)}{\alpha_\ell \lambda_1^D \mathcal{D}(r_1^D) + \lambda_1^L \mathcal{L}(r_1^L)} = \frac{\kappa'(n_{1\ell})}{\kappa'(n_{2\ell})}$$

The conclusion follows from the fact that the left-hand side (i) is strictly increasing in α_ℓ; (ii) is larger than one as α_ℓ grows large; and (iii) is smaller than one as α_ℓ grows small. ■

A.2.5 Proof of Proposition 6

Proof. The first order conditions for Q^D and $\bar{Q}^L$ are

$$\begin{aligned} \lambda_j^D \mathcal{D}\left(r_j^D\right) B^D &= C_D \\ \lambda_j^L \mathcal{L}\left(r_j^L\right) B^L &= C_L \end{aligned}$$

We begin with the ratio of the two first order conditions and the balance sheet constraint

$$\frac{\lambda_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\lambda_j^D \mathcal{D}\left(r_j^D\right) B_j^D} = \frac{C_L}{C_D}$$

$$1 + \omega_j = \frac{\bar{Q}_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\bar{Q}_j^D \mathcal{D}\left(r_j^D\right) B_j^D}$$

Since C is homothetic, $\frac{C_L}{C_D}$ depends only on $\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$. Therefore these equations determine wholesale funding intensity and $\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$. Therefore if B_j^L and B_j^D change in proportion, there is no change in ω_j or $\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$. Given the processing costs θ_j^D and θ_j^L, λ_j^D, λ_j^L, r_j^D, r_j^L only depend on ω, so these are also unchanged. To get at the change in appeal, we differentiate each of the first-order conditions:

$$\begin{aligned}
\frac{\bar{Q}_j^D C_{DD}}{C_D} d\log \bar{Q}_j^D + \frac{\bar{Q}_j^L C_{DL}}{C_D} d\log \bar{Q}_j^L &= d\log B_j^D \\
\frac{\bar{Q}_j^D C_{LD}}{C_L} d\log \bar{Q}_j^D + \frac{Q_L C_{LL}}{C_L} d\log \bar{Q}_j^L &= d\log B_j^L
\end{aligned}$$

Summing the two equations and using $d\log B_j^D = d\log B_j^L = d\log B_j$ along with the fact that $\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$ is unchanged so that $d\log \bar{Q}_j^L = d\log \bar{Q}_j^D$ gives the result:

$$d\log \bar{Q}_j^D = d\log \bar{Q}_j^L = \frac{1}{\varepsilon^C} d\log B_j$$

The rest of the results follow directly from these results and the definitions of z_j^D, z_j^L, D_j, and L_j. ■

A.2.6 Proof of Proposition 7

Proof. As in the proof of Proposition 6, we begin with the ratio of the two first order conditions and the balance sheet constraint

$$\frac{\lambda_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\lambda_j^D \mathcal{D}\left(r_j^D\right) B_j^D} = \frac{C_L}{C_D}$$

$$1 + \omega_j = \frac{\bar{Q}_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\bar{Q}_j^D \mathcal{D}\left(r_j^D\right) B_j^D}$$

Taking logs and differentiating each gives

$$-\left(\varepsilon_j^\lambda + \varepsilon_j^X\right) d\log\left(1+\omega_j\right) + d\log \frac{B_j^L}{B_j^D} = \chi_j d\log \frac{\bar{Q}_j^L}{\bar{Q}_j^D} \tag{31}$$

$$d\log\left(1+\omega_j\right) = d\log \frac{\bar{Q}^L}{\bar{Q}^D} - \varepsilon_j^X d\log\left(1+\omega_j\right) + d\log \frac{B_j^L}{B_j^D} \tag{32}$$

Solving for $d\log \frac{\bar{Q}^L}{\bar{Q}^D}$ gives

$$d\log \frac{\bar{Q}_j^L}{\bar{Q}_j^D} = -\frac{\varepsilon_j^\lambda - 1}{\varepsilon_j^\lambda + \left(1+\chi_j\right)\varepsilon_j^X + \chi_j} d\log \frac{B_j^L}{B_j^D}$$

To get at the change in $\frac{z_j^L}{z_j^D} = \frac{\lambda_j^L \mathcal{L}(r_j^L)\bar{Q}^L}{\lambda_j^D \mathcal{D}(r_j^D)\bar{Q}^D}$, we differentiate

$$d\log\frac{z_L}{z_D} = -\left(\varepsilon_j^{\lambda} + \varepsilon_j^{X}\right) d\log\left(1+\omega_j\right) + d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$$

Using (31), this is

$$\begin{aligned}
d\log\frac{z_L}{z_D} &= \left(\chi_j d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D} - d\log\frac{B_j^L}{B_j^D}\right) + d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D} \\
&= \left(1+\chi_j\right) d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D} - d\log\frac{B_j^L}{B_j^D} \\
&= \left(1+\chi_j\right)\left(-\frac{\varepsilon_j^{\lambda}-1}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j} d\log\frac{B_j^L}{B_j^D}\right) - d\log\frac{B_j^L}{B_j^D} \\
&= -\left[\left(1+\chi_j\right)\frac{\varepsilon_j^{\lambda}-1}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j} + 1\right] d\log\frac{B_j^L}{B_j^D} \\
&= -\left[\frac{\left(2+\chi_j\right)\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}-1}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j}\right] d\log\frac{B_j^L}{B_j^D}
\end{aligned}$$

To get at the change in the ratio of loans to deposits, $\frac{L_j}{D_j} = \frac{\bar{Q}_j^L B_j^L \mathcal{L}(r_j^L)}{\bar{Q}_j^D B_j^D \mathcal{D}(r_j^D)} = (1+\omega_j)$, we have

$$\begin{aligned}
d\log\frac{L_j}{D_j} &= d\log\left(1+\omega_j\right) = \frac{1}{1+\varepsilon_j^{X}}\left(d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D} + d\log\frac{B_j^L}{B_j^D}\right) \\
&= \frac{1}{1+\varepsilon_j^{X}}\left(-\frac{\varepsilon_j^{\lambda}-1}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j} + 1\right) d\log\frac{B_j^L}{B_j^D} \\
&= \frac{1+\chi_j}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j} d\log\frac{B_j^L}{B_j^D} \\
&= \left(1 - \frac{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}-1}{\varepsilon_j^{\lambda}+\left(1+\chi_j\right)\varepsilon_j^{X}+\chi_j}\right) d\log\frac{B_j^L}{B_j^D}
\end{aligned}$$

■

A.3 Details on Limiting Case

A.3.1 A Two-Stage Problem

In this section, we describe the limiting case that is the focus of the paper. Before describing the limit, it will be useful to reframe bank j's problem. Let $\delta_\ell(O_j) \equiv \min_{o\in O_j} \delta_{\ell o}$ be the shortest distance between location ℓ and any of bank j's branches. Let $x_{j\ell}^D \equiv A_\ell^D J_{j\ell}\phi_{j\ell}$ and $x_{j\ell}^L \equiv A_\ell^L J_{j\ell}\phi_{j\ell}$. Then firm j's profit is

$$\pi_j = \sup_{\substack{O_j, D_j, L_j, \omega_j, \\ r_j^D, r_j^L, \bar{Q}_j^D, \bar{Q}_j^L}} \left(r_j^L - \theta_j^L\right) L_j - \left(r_j^D + \theta_j^D\right) D_j - R\left(\omega_j\right)\omega_j D_j - \sum_{o\in O_j} \Psi_o - w_j^* H\left(|O_j|\right) - w_j^* C\left(\bar{Q}_j^D, \bar{Q}_j^L\right)$$

subject to

$$\begin{aligned} D_j &= \bar{Q}_j^D \mathcal{D}\left(r_j^D\right) \int T^D\left(\delta_\ell\left(O_j\right)\right) x_{j\ell}^D d\ell \\ L_j &= \bar{Q}_j^L \mathcal{L}\left(r_j^L\right) \int T^L\left(\delta_\ell\left(O_j\right)\right) x_{j\ell}^L d\ell \\ D_j &= \left(1+\omega_j\right) L_j \end{aligned}$$

We can divide the bank's problem into two stages, first selecting branch locations O_j and then making the remainder of its choices. That is the firm's problem can be expressed as With this, we can characterize the second step as

$$\pi_j = \sup_{O_j} F_j\left(B_j^D(O_j), B_j^L(O_j), B^{fixed}(O_j), B^{span}(O_j)\right)$$

where

$$\begin{aligned} B_j^D\left(O_j\right) &\equiv \int T^D\left(\delta_\ell\left(O_j\right)\right) x_{j\ell}^D d\ell \\ B_j^L\left(O_j\right) &\equiv \int T^L\left(\delta_\ell\left(O_j\right)\right) x_{j\ell}^L d\ell \\ B^{fixed}\left(O_j\right) &\equiv \sum_{o\in O_j} \Psi_o \\ B^{span}\left(O_j\right) &\equiv H\left(|O_j|\right) \end{aligned}$$

and the function F_j is summarizes the optimization in the second step:

$$F_j\left(B^D, B^L, B^{fixed}, B^{span}\right) = \sup_{\substack{D_j, L_j, \omega_j, \\ r_j^D, r_j^L, \bar{Q}_j^D, \bar{Q}_j^L}} \left(r_j^L - \theta_j^L\right) L_j - \left(r_j^D + \theta_j^D\right) D_j - R\left(\omega_j\right)\omega_j D_j - B^{fixed} - w_j^* B^{span} - w_j^* C\big(\bar{Q}_j^D, \bar{Q}$$

subject to

$$\begin{aligned} D_j &= \bar{Q}_j^D \mathcal{D}\left(r_j^D\right) B^D \\ L_j &= \bar{Q}_j^L \mathcal{L}\left(r_j^L\right) B^L \\ D_j &= \left(1+\omega_j\right) L_j \end{aligned}$$

With this, we are in a position to study the limiting economy.

A.3.2 The Limiting Economy

Consider a sequence of models whose parameters are indexed by $\Delta > 0$. In particular, for economy Δ, suppose that household distaste for travelling to a branch for deposits and for loans is given by

$$T^{D,\Delta}(\delta) = t^D\left(\frac{\delta}{\Delta}\right)$$
$$T^{L,\Delta}(\delta) = t^L\left(\frac{\delta}{\Delta}\right)$$

local fixed costs are given by

$$\Psi_\ell^\Delta = \psi_\ell \Delta^2$$

and the headquarter cost is given by

$$H^\Delta(|O_j|) = h\left(\Delta^2|O_j|\right).$$

Thus for an economy with a small Δ, households have a strong distaste for traveling to branches, and fixed and span of control costs are small. These jointly imply that it is optimal for a bank to set up many branches.

Our aim is to characterize the bank's profit and choices in the limiting economy as $\Delta \to 0$. Let π_j^Δ be firm j's profit in economy Δ. Proposition A.8 shows the firms profit in the limiting economy

Proposition A.8 *Let $\mathcal{N}$ be the set of positive functions $n : \mathcal{S} \to [0, \infty)$. In the limit, the bank's profit converges to*

$$\lim_{\Delta\to 0} \pi_j^\Delta = \sup_{n_j\in\mathcal{N}} F_j\left(b_j^D(n_j), b_j^L(n_j), b^{fixed}(n_j), b^{span}(n_j)\right)$$

where

$$\begin{aligned} b_j^D(n_j) &\equiv \int \kappa^D(n_{j\ell})x_{j\ell}^D d\ell \\ b_j^L(n_j) &\equiv \int \kappa^L(n_{j\ell})x_{j\ell}^L d\ell \\ b^{fixed}(n_j) &\equiv \int n_{j\ell}\psi_\ell d\ell \\ b^{span}(n_j) &\equiv h\left(\int n_{j\ell} d\ell\right) \end{aligned}$$

where $\kappa^D(n) \equiv ng^D\left(\frac{1}{n}\right)$ and $\kappa^L(n) \equiv ng^L\left(\frac{1}{n}\right)$, and $g^D(u)$ and $g^L(u)$ are integrals of the functions $t^D(\cdot)$ and $t^L(\cdot)$ respectively over all distances between the origin and points of a regular hexagon of area u centered at the origin.

The proof follows largely along the lines of Oberfield et al. (2024).

A.4 A Convenient Functional Form

Suppose that the intensive margins of deposit and loan demand take the forms

$$\begin{aligned}\mathcal{D}(r) &= \left(r-\bar{r}^{D}\right)^{\frac{1}{\beta^{D}}-1}\\ \mathcal{L}(r) &= \left(\bar{r}^{L}-r\right)^{\frac{1}{\beta^{L}}-1}\end{aligned}$$

with β^D, $\beta^L \in (0,1]$ and $\bar{r}^D$ and $\bar{r}^L$ are some reference rates. Then the solution to the interest rate setting problems $r^D = \max_r (c-r)\mathcal{D}(r)$ and $r^L = \max_r (r-c)\mathcal{L}(r)$ are

$$\begin{aligned}r^{D} &= \beta^{D}\bar{r}^{D}+\left(1-\beta^{D}\right)c \quad \text{(as long as } c \geq \bar{r}^{D}\text{)}\\ r^{L} &= \beta^{L}\bar{r}^{L}+\left(1-\beta^{L}\right)c \quad \text{(as long as } \bar{r}^{L} \geq c\text{)}\end{aligned}$$

In the model, the shadow payoff of deposits is $\rho^D(\omega_j) - \theta_j^D$, while the shadow cost of loans is $\rho^L(\omega_j) + \theta_j^L$, so that the multipliers are would be

$$\begin{aligned}\lambda_j^D &= \rho^D(\omega_j) - r_j^D - \theta_j^D = \beta^D\left[\rho^D(\omega_j) - \theta_j^D - \bar{r}^D\right]\\ \lambda_j^L &= r_j^L - \theta_j^L - \rho^L(\omega_j) = \beta^L\left[\bar{r}^L - \theta_j^L - \rho^L(\omega_j)\right]\end{aligned}$$

Finally, maximized objective of each interest rate setting problem takes the form

$$\begin{aligned}\max_r[\rho^D(\omega_j) - r - \theta_j^D]\mathcal{D}(r) &= \beta^D(1-\beta^D)^{\frac{1}{\beta^D}-1}[\rho^D(\omega_j) - \theta_j^D - \bar{r}^D]^{\frac{1}{\beta^D}}\\ \max_r[r - \theta_j^L - \rho^L(\omega_j)]\mathcal{L}(r) &= \beta^L(1-\beta^L)^{\frac{1}{\beta^L}-1}[\bar{r}^L - \theta_j^L - \rho^L(\omega_j)]^{\frac{1}{\beta^L}}\end{aligned}$$

A.5 Additional Empirical Results

A.5.1 Density of Initial Location and Bank Expansion

We consider the following regressions,

$$\log(\mathbb{E}[Y_{j,T_j} - Y_{j,0_j}]) = \beta\log(\text{Density}_{c_j^{HQ},0_j}) + \delta\text{Size}_{j,0_j} + \alpha\log(Y_{j,0_j}) + \gamma_{T_j}\times\gamma_{0_j} + \gamma_{s_j^{HQ}} + \varepsilon_j\ , \tag{33}$$

$$\log(Y_{j,T_j}) - \log(Y_{j,0_j}) = \beta\log(\text{Density}_{c_j^{HQ},0_j}) + \delta\text{Size}_{j,0_j} + \alpha\log(Y_{j,0_j}) + \gamma_{T_j}\times\gamma_{0_j} + \gamma_{s_j^{HQ}} + \varepsilon_j\ . \tag{34}$$

In these regressions, $\text{Density}_{c_j^{HQ},0_j}$ is the population density of bank j's headquarter county in the first year they are included in the sample, 0_j; $\text{Size}_{j,0_j}$ is the log of bank j's total deposits in their initial sample year; γ_{T_j} and γ_{0_j} are fixed effects for the final and initial sample year of bank j; and $\gamma_{s_j^{HQ}}$ is a fixed effect for bank j's headquarter state. We let $Y_{j,\cdot}$ denote either the number of branches of bank j or the number of active counties. Both headquarter density and bank size are standardized.

We include the final-initial year fixed effects to account for the fact that some banks exited or entered the sample at different times. Comparing a bank that operated throughout the entire sample period to one that entered halfway through would therefore bias the results. We also include the state headquarters fixed effect to account for differences in regulation at the state level. A bank in New York, which deregulated in the early 1980s, would have had more expansion opportunities than a bank in Kentucky, which deregulated in the middle of the 1990s. Therefore, differences in headquarter county density may in turn be correlated with the deregulation. The fixed effect absorbs these differences. Finally, we include initial bank size controls to account for differences in initial banking technology and appeal.

The results are presented in Table VIII. Panel A presents the results for the Poisson regressions (33) and Panel B presents the results for the regression in log changes (34). We consider three specifications. In Columns (1) and (4), we do not include bank size controls. We add the controls in Columns (2) and (5). In Columns (3) and (6) we consider a more rigid specification that interacts the headquarters state fixed effect with the final-initial year fixed effect. This specification effectively compares two similar sized banks headquartered in the same state and existing in the same part of the sample, but headquartered in different counties.

Across all specifications, we find that being headquartered in a denser county is positively and significantly associated with (i) adding more branches and accessing more counties, and (ii) having a higher growth rate for the number of branches and counties. The results support the notion that banks face increasing returns to scale, which at least in part explains the substantial growth of the largest banks headquartered in big cities such as Bank of America or Chase.

A.5.2 Local Appeal for Banks and Distance

We have allowed local appeal to depend on distance from headquarters. To estimate the extent to which distance reduces appeal, we assess the extent to which, conditional on the number of branches, a bank's deposits (or equivalently deposits per branch) falls with distance, conditional on location and bank fixed effects.

Bank j's deposits per branch in location ℓ as

$$\frac{D_{j\ell}}{n_{j\ell}} = \bar{Q}_j^D J_{j\ell}^D \phi_{j\ell} A_\ell^D \mathcal{D}\left(r_j^D\right) \frac{\kappa^D\left(n_{j\ell}\right)}{n_{j\ell}}$$

This suggests the following regression specification

$$\log \frac{D_{j\ell}}{n_{j\ell}} = [\text{Location FEs}] + [\text{Firm FEs}] + [\text{polynomial of } n] + \beta \times \text{dist from headquarters} + \epsilon_{j\ell}$$

β will tell us how $Q_{j\ell}$ varies with distance. As shown in Table IX, we find $\beta < 0$ across all specifications,

Panel A: Levels (Poisson)						
	Number of Branches			Number of Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Density}_{c_j^{HQ},0_j})$	1.281***	0.231***	0.200***	0.906***	0.119***	0.084*
	(0.127)	(0.064)	(0.059)	(0.094)	(0.044)	(0.047)
$\log(Y_{j,0_j})$		0.371***	0.501***		0.337***	0.433***
		(0.079)	(0.087)		(0.065)	(0.070)
$\text{Size}_{j,0_j}$		0.785***	0.743***		0.806***	0.831***
		(0.096)	(0.083)		(0.050)	(0.049)
$\gamma_{T_j} \times \gamma_{0_j}$	✓	✓		✓	✓	
$\gamma_{s_j^{HQ}}$	✓	✓		✓	✓	
$\gamma_{T_j} \times \gamma_{0_j} \times \gamma_{s_j^{HQ}}$			✓			✓
Observations	16,075	16,056	12,637	16,114	16,095	9,862
Pseudo-R^2	0.47	0.78	0.85	0.36	0.62	0.67

Panel B: Logs						
	Number of Branches			Number of Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Density}_{c_j^{HQ},0_j})$	0.090***	0.079***	0.090***	0.040***	0.022***	0.023***
	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)
$\log(Y_{j,0_j})$		−0.174***	−0.181***		−0.074***	−0.064***
		(0.010)	(0.012)		(0.014)	(0.016)
$\text{Size}_{j,0_j}$		0.140***	0.166***		0.104***	0.116***
		(0.008)	(0.009)		(0.005)	(0.006)
$\gamma_{T_j} \times \gamma_{0_j}$	✓	✓		✓	✓	
$\gamma_{s_j^{HQ}}$	✓	✓		✓	✓	
$\gamma_{T_j} \times \gamma_{0_j} \times \gamma_{s_j^{HQ}}$			✓			✓
Observations	18,077	18,055	15,763	18,077	18,055	15,763
Within-R^2	0.01	0.04	0.05	0.00	0.04	0.04

Table VIII: This table displays the results of the pseudo-Poisson regression equation (33) (Panel A) and regression equation (34) (Panel B). The dependent variables are either the total/log change in number of branches or number of counties for bank j between the first and last year bank j is in the sample. $\log(\text{Density}_{c_j^{HQ},0_j})$ is the log population density of bank j's headquarters county in the initial sample year. $\text{Size}_{j,0_j}$ is the log of total deposits of bank j in the initial sample year. $Y_{j,0_j}$ is the initial number of bank j's branches/counties. Columns (1) and (4) only consider headquarter density, while Columns (2) and (5) controls for initial bank deposits and branches/counties. Columns (3) and (6) interact the headquarter state fixed effect with the final-initial year fixed effects. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	$\log\left(\frac{Dep_{j\ell}}{n_{j\ell}}\right)$			$\log(Dep_{j\ell})$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Distance}_{j\ell})$	-0.127^{***}	-0.132^{***}	-0.124^{***}	-0.264^{***}	-0.276^{***}	-0.271^{***}
	(0.011)	(0.011)	(0.014)	(0.017)	(0.018)	(0.022)
County × Year FEs	✓	✓	✓	✓	✓	✓
Bank × Year FEs	✓	✓	✓	✓	✓	✓
$n_{j\ell}$ Polynomial	✓	✓	✓	✓	✓	✓
Top 10% of Banks		✓			✓	
Top 1% of Banks			✓			✓
Observations	169,408	134,675	70,873	169,408	134,675	70,873
R^2	0.81	0.81	0.83	0.69	0.65	0.70
Within R^2	0.03	0.03	0.03	0.18	0.20	0.22

Table IX: This table displays regression results of equation XX. The dependent variables are the log of bank j's deposits in county ℓ divided by their branch density [Columns (1)-(3)] and the log of bank j's total deposits in county ℓ [Columns (4)-(6)]. Distance$_{j\ell}$ is the total miles between the centroid of bank j's headquarter county and county ℓ. All specifications are restricted to banks that are active in at least 2 counties in a given year. Specifications (2) and (5) restrict the sample to the top 10% of banks by total deposits and specifications (3) and (6) restrict the sample to the top 1% of banks by total deposits. Controls are a cubic polynomial in branch density $n_{j\ell}$. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

suggesting that appeal declines with distance.

A.5.3 Absolute Sorting In the Data

In this section, we test for absolute sorting. We use the following specification:

$$\text{Size}_{ct} = \beta \log(\text{Density})_{ct} + \gamma_{st} + \varepsilon_{cst} \tag{35}$$

	Dependent variable: Size_{ct}			
	(1)	(2)	(3)	(4)
$\log(\text{Density}_{ct})$	0.536^{***}	0.504^{***}	0.257^{***}	0.443^{***}
	(0.004)	(0.005)	(0.006)	(0.003)
$\log(\text{Density}_{ct}) \times \text{OOS}_{ct}$				-0.298^{***}
				(0.007)
OOS_{ct}				5.056^{***}
				(0.031)
No Headquarters		✓		
Out-of-State Only			✓	
Observations	80,165	71,965	35,528	114,719
R^2	0.70	0.62	0.49	0.77
Within R^2	0.25	0.17	0.05	0.65

Table X: This table displays regression results for equation (35). The dependent variable is the average branch-weighted bank size in county c in year t. Density_{ct} is the population density of county c in year t. OOS_{js} is an indicator for banks that are not headquartered in state s. Heteroscedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

where $\log(\text{Density})_{ct}$ is the log population density of county c at time t, γ_{st} is a state-year fixed effect, and $\log(\text{Size})_{ct}$ is defined as

$$\text{Size}_{ct} = \sum_{j \in \mathcal{J}_{ct}} \left(\frac{b_{jct}}{\sum_{j \in \mathcal{J}_{ct}} b_{jct}} \right) \text{Size}_{jt}.$$

As in Section 5.1, we consider four specifications. First, we estimate the regression with no restrictions. Second, we restrict branches to be those outside of a bank's headquarter county. Third, we only consider the average size of out-of-state banks. Fourth, we include an interaction term for out-of-state banks.

Table X reports the results. In all specifications, we find evidence for absolute sorting, $\beta > 0$. Out-of-state banks again sort less than in-state banks, though are relatively more prevalent in dense counties than in-state banks.

A.5.4 In and Out of State Branch Changes Across Population Deciles

We decompose the growth in branches into an out-of-state component (o) and an in-state component (i) using the following decomposition:

$$\frac{b_{gc2006} - b_{gc1981}}{b_{gc1981}} = \underbrace{\frac{b^o_{gc2006} - b^o_{gc1981}}{b_{gc1981}}}_{\text{out-of-state growth}} + \underbrace{\frac{b^i_{gc2006} - b^i_{gc1981}}{b_{gc1981}}}_{\text{in-state growth}}$$

where c denotes a population density ventile and g denotes the bank size group. Figure A.13 shows the results of the decomposition. For the bottom 90% of the bank size distribution, out-of-state branching was not a significant factor in growth. However, for the largest banks, out-of-state growth was strong and in some cases outpaced in-state branch growth. This was especially the case for the top 1% of banks: in every density ventile, out-of-state branch growth was large and in most ventiles, in-state growth was negative.[50]

A.5.5 Persistence of Local Deposit/Loan Ratio

This section reports the persistence of a yearly measure of D/L. Specifically, define

$$(D/L)_{ct} \equiv \frac{\text{Deposits}_{ct}}{\text{Small Business Loans}_{ct}}.$$

We consider three measures of persistence. First, we compute the raw autocorrelation between $(D/L)_{ct}$ and $(D/L)_{ct-k}$ for $k = 1, \ldots, 10$. Second, we report the slope coefficients $\{\beta_k\}_{k=1}^{10}$ of the regression

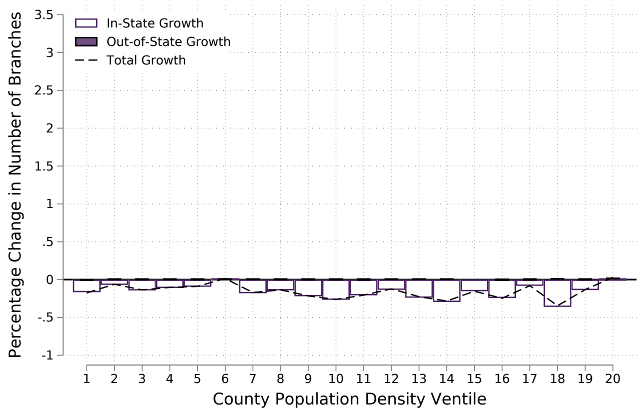
$$(D/L)_{ct} = \alpha_k + \beta_k (D/L)_{ct-k} + \varepsilon_{ct}. \tag{36}$$

Third, we report the adjusted R^2 of each of the regressions above. Figure A.14 reports the results graphically. D/L displays significant persistence over time, even at long time horizons.

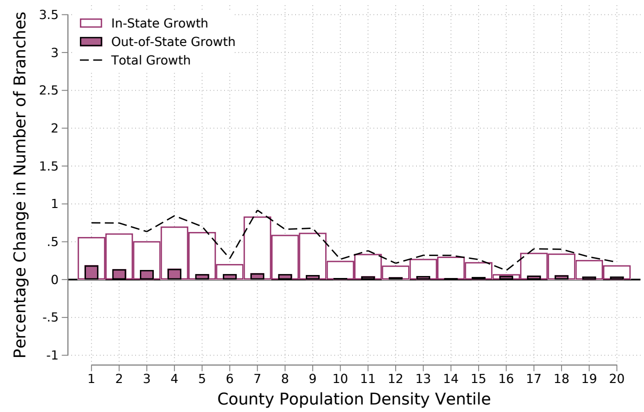
A.5.6 Numerical Results for Local Projections

This section reports the estimated coefficients for the local projections (27) in Table XI.

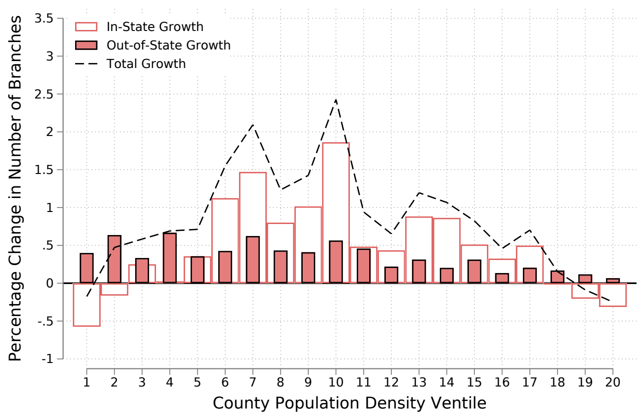
[50] Note that this does not imply large banks reduced the number of branches in their in-state counties, but rather large out-of-state banks consolidated with large in-state banks, reducing the number of large in-state bank branches in these counties.



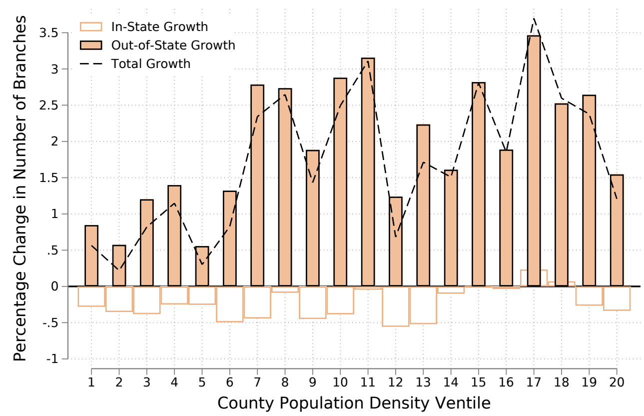
(a) Bottom 50% of Banks



(b) 50-90th Percentile of Banks

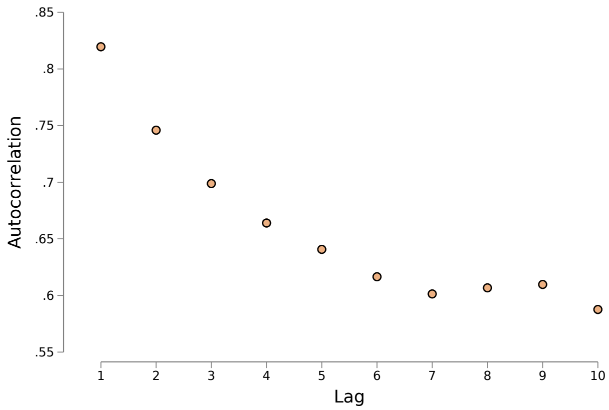


(c) 90-99th Percentile of Banks

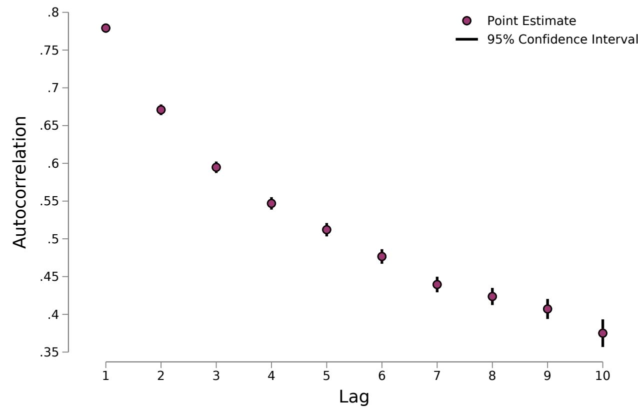


(d) Top 1% of Banks

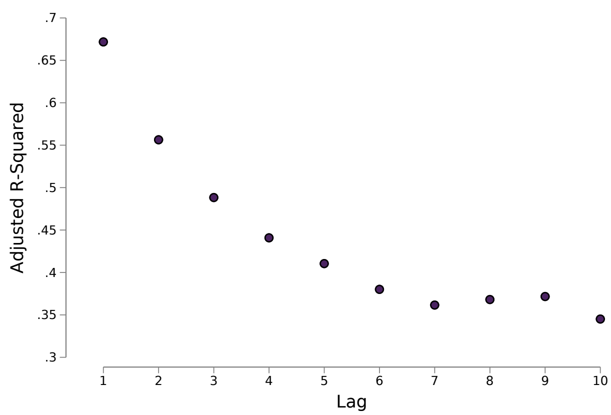
Figure A.13: This figure displays branch expansion by county population density and bank size. Dashed lines display total branch growth of banks within a given size bin in a given density ventile. White bars display the in-state branch growth component and colored bars display the out-of-state branch growth component. Bank size bins are the bottom 50%, the 50-90th percentile, the 90-99th percentile, and the top 1% of banks by deposits.



(a) Raw Autocorrelation



(b) Regression Autocorrelation



(c) Regression Adjusted R^2

Figure A.14: This figure plots three measures of the autocorrelation in deposit-to-loan intensity (D/L). Panel (a) plots the raw correlation, Panel (b) plots the slope coefficients from equation (36), and Panel (c) plots the adjusted R^2 from the regression.

	Wholesale Funding Exposure							Branches							Counties						
$h = \ldots$	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Recip	-0.01‡	-0.01†	-0.01*	-0.01	-0.00	0.00	0.01*	-0.01	-0.51	-0.50	-0.41	-1.30	-2.17	-3.34*	-0.10*	-0.16†	-0.24†	-0.48†	-0.73†	-1.02†	-1.22†
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.22)	(0.38)	(0.62)	(0.92)	(1.22)	(1.63)	(1.96)	(0.05)	(0.08)	(0.11)	(0.18)	(0.28)	(0.40)	(0.50)
Recip × WFE	0.07‡	0.07*	0.05	0.02	-0.01	-0.02	-0.04	0.70	1.90†	3.61‡	5.15‡	6.22‡	6.99‡	7.69‡	0.24†	0.45†	0.73†	0.99†	1.27†	1.48†	1.66†
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.034)	(0.65)	(0.90)	(1.30)	(1.73)	(1.92)	(2.19)	(2.50)	(0.11)	(0.19)	(0.31)	(0.43)	(0.55)	(0.59)	(0.63)
Recip × Large	0.03‡	0.05‡	0.06‡	0.06‡	0.07‡	0.09‡	0.10‡	-5.90	-12.8	-10.7	-9.59	-9.10	-23.8	-34.6	-1.31†	-2.17	-2.71	-1.45	−1.11	-1.67	-2.43
	(0.007)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.031)	(2.68)	(8.25)	(13.6)	(12.4)	(15.4)	(18.6)	(30.4)	(0.65)	(1.45)	(2.49)	(3.47)	(4.89)	(5.36)	(6.51)
Recip × WFE × Large	-0.16‡	-0.27‡	-0.30‡	-0.30‡	-0.31†	-0.32‡	-0.31‡	67.2†	144.8†	190.8*	213.5*	253.5	362.0*	450.3*	21.6‡	42.8‡	61.0‡	68.9†	85.2†	105.7†	126.4†
	(0.05)	(0.07)	(0.09)	(0.11)	(0.12)	(0.10)	(0.089)	(26.1)	(64.2)	(95.8)	(127.2)	(159.7)	(197.7)	(262.0)	(6.15)	(12.8)	(20.1)	(27.2)	(37.3)	(45.8)	(58.9)
WFE	-0.28‡	-0.49‡	-0.65‡	-0.75‡	-0.82‡	-0.88‡	-0.93‡	0.33	-0.50	-1.50	-2.08	-2.17	-1.99	-1.70	0.02	-0.13	-0.21	-0.25	-0.26	-0.32	-0.41
	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)	(0.021)	(0.65)	(1.06)	(1.64)	(2.19)	(2.34)	(2.36)	(2.05)	(0.08)	(0.11)	(0.14)	(0.19)	(0.25)	(0.28)	(0.29)
WFE × Large	0.07†	0.11†	0.11*	0.12*	0.11†	0.11†	0.07	-19.7	-49.9	-89.4	-123.0	-166.3	-187.1	-202.8	-8.30	-18.9*	-30.9*	-46.8*	-65.7*	-79.4	-90.5
	(0.03)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.064)	(21.1)	(47.5)	(83.7)	(120.6)	(167.1)	(218.9)	(265.5)	(5.03)	(11.2)	(17.9)	(26.9)	(38.0)	(48.3)	(58.2)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	127962	117150	107549	98762	90574	82963	75776	128014	117226	107635	98848	90655	83040	75846	128014	117226	107635	98848	90655	83040	75846
Adjusted R^2	0.18	0.34	0.44	0.52	0.57	0.63	0.68		0.23	0.36	0.47	0.57	0.63	0.69	0.06	0.18	0.28	0.36	0.45	0.50	0.56
Within R^2	0.12	0.23	0.30	0.36	0.40	0.42	0.45	0.01	0.01	0.02	0.02	0.03	0.03	0.04	0.02	0.04	0.06	0.07	0.09	0.11	0.12

Table XI: This table reports numerical results for equation (27). The first section reports the results for $Y_{jt} = \text{WFE}_{jt}$, the second section reports the results for $Y_{jt} = \text{branches}_{jt}$, and the third section reports results for $Y_{jt} = \text{counties}_{jt}$. Recip_{jt} is the fraction of states that a bank headquartered in state $s(j)$ can enter at time t. WFE_{jt} is the wholesale funding exposure of bank j in year t. Large_j is an indicator for whether bank j is in the top 5% of banks by deposits in 1984. Standard errors are reported in parentheses and are clustered at the headquarter-state level. * $p < 0.1$, † $p < 0.05$, ‡ $p < 0.01$.

B Data Appendix

This section outlines the cleaning procedure for the data. We begin by appending the Summary of Deposits data from 1981-1993 provided by Christa Bouwman to the publicly available data from 1994-2006 provided by the FDIC. The initial data set has 1,894,507 branch-year observations. We then construct our initial sample by performing the following operations:

1. Drop banks with bank identifier = 0 [23 observations]
2. Drop branches with no deposits [95,973 observations]
3. Drop branches outside of the US [11,751 observations]
4. Drop non-continental US states (AK, HI) and DC [13,143 observations]
5. Drop banks supervised by the OTS since the 1981-1993 data do not include these banks [131,297 observations]

After the initial cleaning, there are 1,642,320 observations remaining. We then perform several operations to match banks to their holding companies. The data present two challenges. First, data on holding company locations begin in 1986, five years after the sample starts. We therefore need to infer holding company locations for 1981-1985 from the initial data in 1986. Second, several small firms appear to be acquired by a new holding company that only owns a single firm. We need to identify whether these were actual acquisitions or whether a given small bank simply created a holding company for legal purposes and owned only the bank in question. We clean the data according to the following process.

Step 1: Clean Addresses We first need to make sure that branch, bank, and BHC addresses are consistent through time. We clean the addresses according to the following steps. We demonstrate the process using an example address, "#232 w elm street, campus".

1. Replace raw address with proper capitalization [→ #232 W Elm Street, Campus]
2. Remove "#" and "." characters [→ 232 W Elm Street, Campus]
3. Replace directional characters with their full name [→ 232 West Elm Street, Campus]
4. Shorten streets, avenues, boulevards, roads, and drives to their abbreviations [→ 232 West Elm St, Campus]
5. Remove text after trailing commas [→ 232 West Elm St]

At this point, we treat addresses as unique within the county.

Step 2: Identify Bank-BHC Pairs We next merge the cleaned BHC addresses to each BHC identifier in the data. To identify banks that became BHCs, we perform the following procedure.

1. Collapse the data down to the bank-BHC-year level
2. Carry BHC variables (name, address, county, state) backwards to 1981-1985
3. Identify changes from no BHC ownership (BHC identifer = 0) to BHC ownership (BHC identifier $\neq$ 0)
4. Use bigram matching between bank headquarter address and BHC headquarter address to identify new vs. existing BHCs. We consider addresses to be the same if their similarity score is above 0.6. We manually inspect the results of this procedure and find that 0.6 correctly captures the majority of legal (non-new) bank-BHC pairs.
5. Replace the BHC identifier with the eventual BHC if (i) the addresses match according to step 4 and (ii) BHC = 0 initially.
6. Repeat Step 2 for BHCs identified in Step 5.
7. If BHC identifier was not replaced, we interpret the change in identifier as an acquisition. Prior to this event, we replace the BHC identifier with the bank identifier and replace BHC name, address, county, and state with that of the bank.

We then merge the cleaned BHC identifiers into the main data set.

Step 3: Clean Missing BHC State Codes Despite the cleaning process in **Step 2**, there are still several small companies in the BHC data that never report geographic variables. This is an important omission since we would like to identify out-of-state banks and distance from headquarters. We infer the headquarters state from a BHC by collapsing the data down to the BHC-year-state level. For all BHCs that are at some point only active in a single state, we replace the missing headquarters state with the state in which the BHC is active. We drop the remaining BHCs that are not matched to a headquarters state, resulting in 20,439 dropped observations. The final data set has 1,629,881 branch-year observations.