Banks in Space*

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Abstract

We study the spatial expansion of banks in response to the banking deregulation of the 1980s and 90s in order to develop a spatial theory of banking. 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.

JEL: G21, R32, L22, L23

Keywords: Multi-establishment firms, Spatial sorting, Branches, Firm location, Span-of-control

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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 interstate 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 (e.g., brokered deposits, interbank loans, foreign deposits, and commercial paper, among other funding types). We show that the top 1% of banks used wholesale 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 also show that the relative 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

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

platforms and information and communication technologies.[2]

Our findings underscore the presence of two forms of sorting. The first one results from span-of-control management costs. Large, productive banks are reluctant to place branches in small markets because they consume management time that could be dedicated to other, more profitable, locations. While those profitable locations entail larger fixed costs in terms of rents and other local costs, productive banks value the higher market size and care relatively less about these local fixed costs. In contrast, small banks are dissuaded from larger markets because of the high local fixed costs, but are not dissuaded from operating branches in smaller markets because they only manage a small number of branches, so their span-of-control costs are small or negligible. 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, so part of a bank's objective is to minimize their use.[3] Because demand for loans and supply of retail deposits vary 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.[4] 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

[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 Call Reports and on county-level population and per-capita income from the U.S. Census and the BEA.

[3]Wholesale funds can be more expensive because they are junior to deposits, because of a variety of government regulations in the wholesale market, or because deposits entail a service benefit for consumers. We take the interest rates faced by banks in the wholesale funds market as given.

[4]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.)

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 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.[5] 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 locations to set up branches 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.[6] 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, consistent with the empirical finding that banks predominantly set uniform deposit and lending rates across branches.[7]

The core of the model is the bank's location decisions for its 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

[5]As Sakong and Zentefis (2023) document, although online and mobile banking have 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.

[6]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).

[7]See Radecki (1998), Heitfield (1999), Heitfield and Prager (2004), Biehl (2002), Park and Pennacchi (2008), Yankov (2024), Granja and Paixao (2023), and Begenau and Stafford (2022).

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 lender has more local branches.[8] Using data from the recent fracking boom, Gilje et al. (2016) argue that distance is also important in mortgage markets.[9] 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.[10] 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.[11] Finally, D'Amico and Alekseev (2025) uses a spatial framework, but without branch location decisions, to study the effect of rising interest rates on bank lending in the period before the geographic banking deregulation.

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 (2023), and Cao et al. (2019). Location choices of multi-plant 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

[8]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.

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

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

[11]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.

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).[12] These papers have been motivated by the observation 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, which are at the core of the new spatial theory of retail banking that we propose.

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 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

[12] See also Bilal (2023); Lindenlaub et al. (2022); Mann (2023); Oh (2023). Wenning (2023) models the sorting of multi-region insurance firms across locations, with an emphasis on how these decisions are affected by uniform pricing rules.

became Bank of America. By 1930, Bank of America had 453 branches throughout the state of California.[13]

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 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.[14] 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.[15]

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.[16] 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 exponentially until 1991 when about half of all potential agreements had been signed.[17] 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. Interstate banking restrictions effectively ended with the passage of the Riegle-Neal Act of 1994, also known as the Interstate Bank Branching Efficiency Act (IBBEA), which 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.[18] 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

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

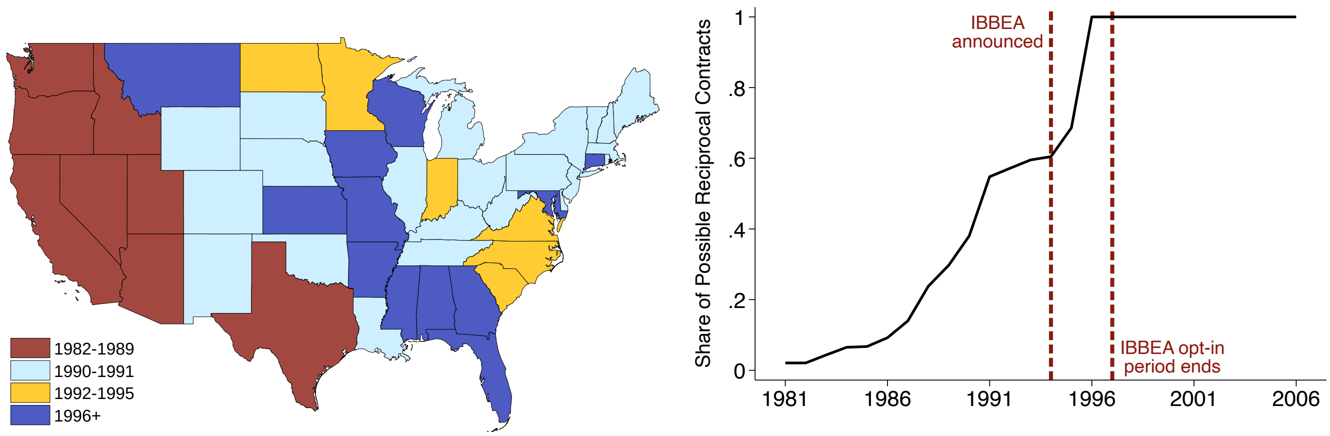
[14] The Bank Holding Company Act of 1956 was, however, enacted primarily to separate banks from other financial institutions such as insurance. See Bank Holding Company Act of 1956 (1956) for more details.

[15] 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).

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

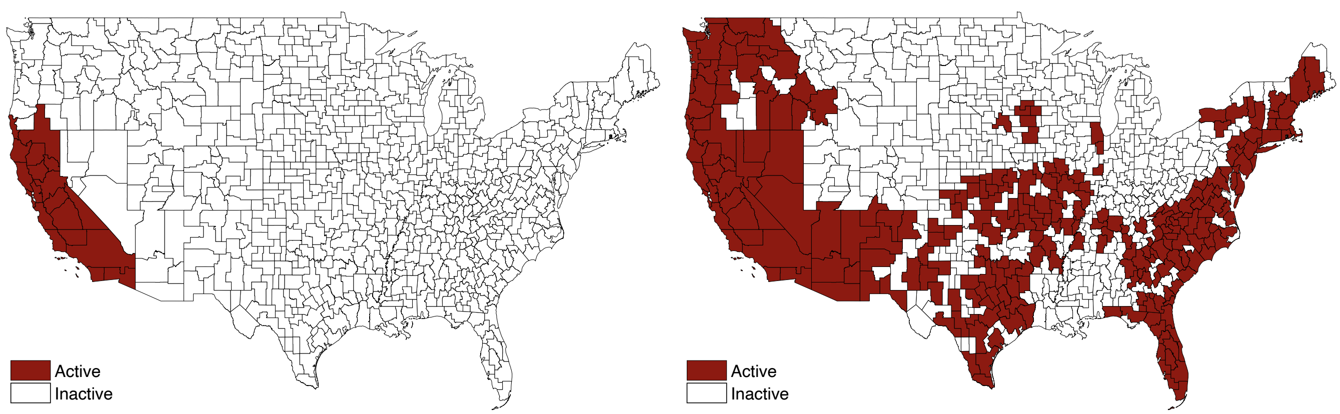
[17] The temporary slowdown in agreements in 1991 was not the result of additional institutional changes but rather the slowdown of national and regional agreements after several states had decided to deregulate nationally while other states had yet to start the process.

[18] 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.



(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.



(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.

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.[19] 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

[19] 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.

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 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.[20] Since the historical data do not cover banks regulated by the Office of Thrift and Supervision, we exclude these banks from the analysis.[21] Each bank branch in the data has a corresponding US county code, which we use as our geographic unit of analysis. Second, we collect data on bank-level liabilities from the Report of Condition and Income (Call Reports). We use bank liabilities to construct a measure of wholesale funding exposure, which we describe later in this section.

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 C.1.

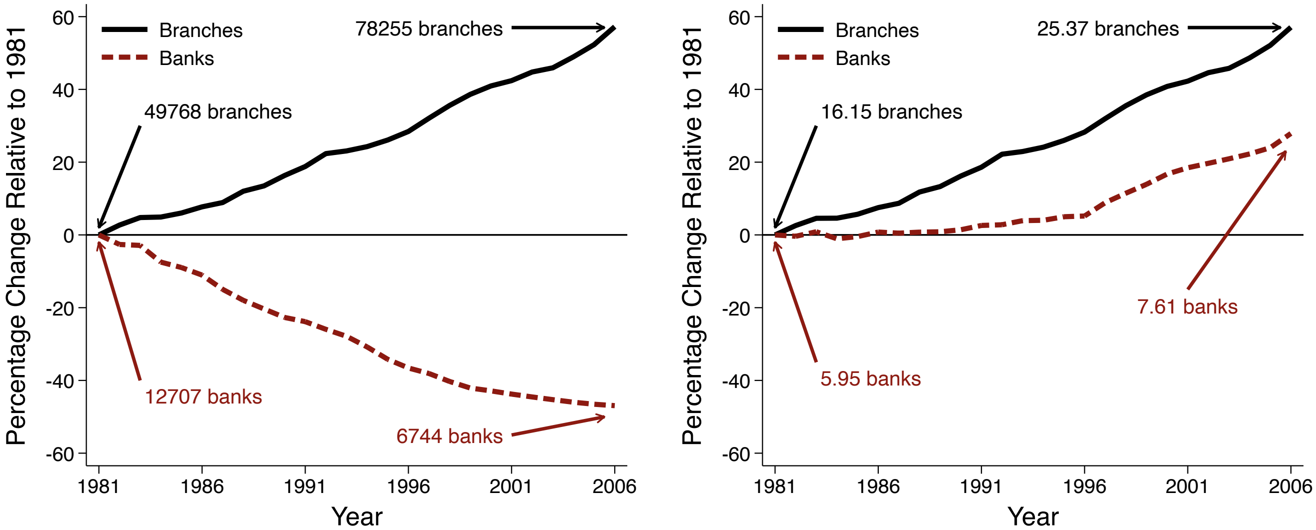
We supplement the banking data with county-level income, population, and demographic measures. Population and demographic data come from the yearly county-level Census population estimates from 1980-2006. Per-capita income data come from the Bureau of Economic Analysis' EconProfile data set.

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

[20] The FDIC provides data from 1994 to the present. We supplement the FDIC data with historical Summary of Deposits data from 1981 to 1993 provided by Christa Bouwman.

[21] 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 red 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.

branches over time. The number of bank branches in the U.S. grew by nearly 60% between 1981 and 2006, 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.[22]

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 (branches per county) and extensive

[22]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.

margin (number of counties), 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 group g. The extensive margin directly measures the change in the average number of active counties.[23] We reassign banks to groups in each year.

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 10% of banks increased by about 61 log points (83%). Branches of the bottom 90% only increased by 14 log points (15.3%). Second, the extensive margin component — the banks' geographic expansion or contraction —dominated for the top 10% of banks, accounting for 76% of total branch growth. Conversely, the intensive margin component — banks' expansion or contraction within each county — dominated for the bottom 90% of banks, accounting for nearly all of their branch growth.

The fast expansion in the number of branches of top banks implied that an increasing share of all branches was concentrated in the top 10% of banks by total deposits. Figure 5 emphasizes how the top 10% of banks in total deposits grew their share of total branches. Their share increased from about 62% to 72% of all branches between 1981 and 2006, which was the result of the 83% increase in the total number of branches across this period for the top 10% of banks.

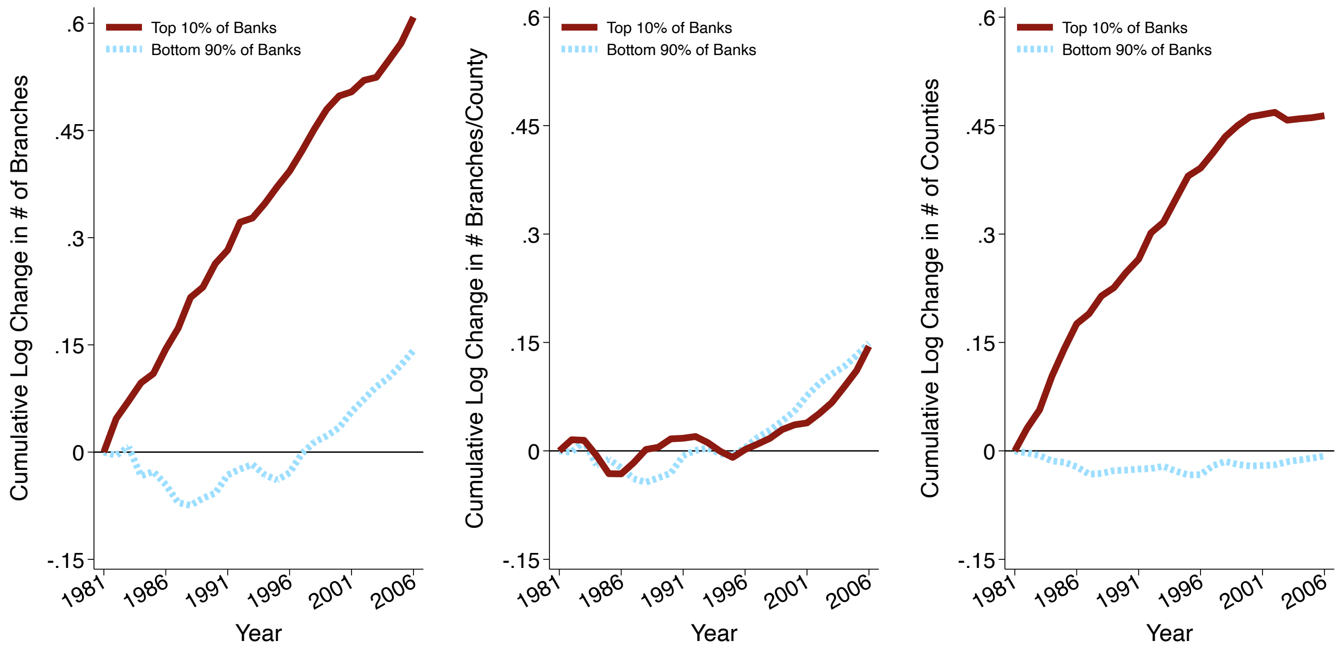
2.2.3 Basic Patterns: Large Banks Use More Wholesale Funding

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. Examples of wholesale funding include brokered deposits, interbank loans, foreign deposits, Fed funds, and commercial paper. 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.[24]

We start by documenting the use of wholesale funding across the bank size distribution in 1981. To avoid selecting particular types of wholesale funds, we measure wholesale funding exposure as the ratio of

[23] 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.

[24] 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.



(a) Branch Growth (b) Branch per County Growth (c) County Growth

Figure 4: This figure plots total branch growth for two bank size bins. The size bins are the bottom 90% of banks and the top 10% of banks by total deposits within a given year. Panel (a) displays cumulative log changes in total branches for each size group, panel (b) displays the cumulative log change in branches per county, and panel (c) displays the cumulative log change in the number of active counties within each size group.

a bank's non-deposit liabilities to its deposits, namely,[25]

$$\text{WFE}_{jt} = \frac{\text{Liabilities}_{jt} - \text{Deposits}_{jt}}{\text{Deposits}_{jt}}. \tag{1}$$

Figure 6a documents the distribution of log wholesale funding exposure, $\log \text{WFE}_{jt}$, across banks in each size bin. A higher value for WFE_{jt} indicates that, conditional on a bank's size, it uses a relatively high amount of wholesale funds. The distribution for the largest 10% of banks is clearly shifted toward higher levels of wholesale funding exposure relative to the bottom 90% of banks, indicating that wholesale funding is typically used by large banks and only rarely used intensively by smaller banks.

Figure 6b displays the equal-weighted average log wholesale funding exposure for each bank size group between 1981 and 2006. While all banks tended to use wholesale funding more intensively after the 1990s, the largest 10% of banks used wholesale funding less intensively *relative* to the bottom 90% by the end of

[25] This value can in principle be greater than 1. However, most values above one are very small unit banks, so we exclude banks whose non-deposit liabilities exceed their deposits from our primary sample. This results in dropping 1,676 (0.7%) bank-year observations from the sample. We verify in Section 4 that the omitted banks do not change our primary results.

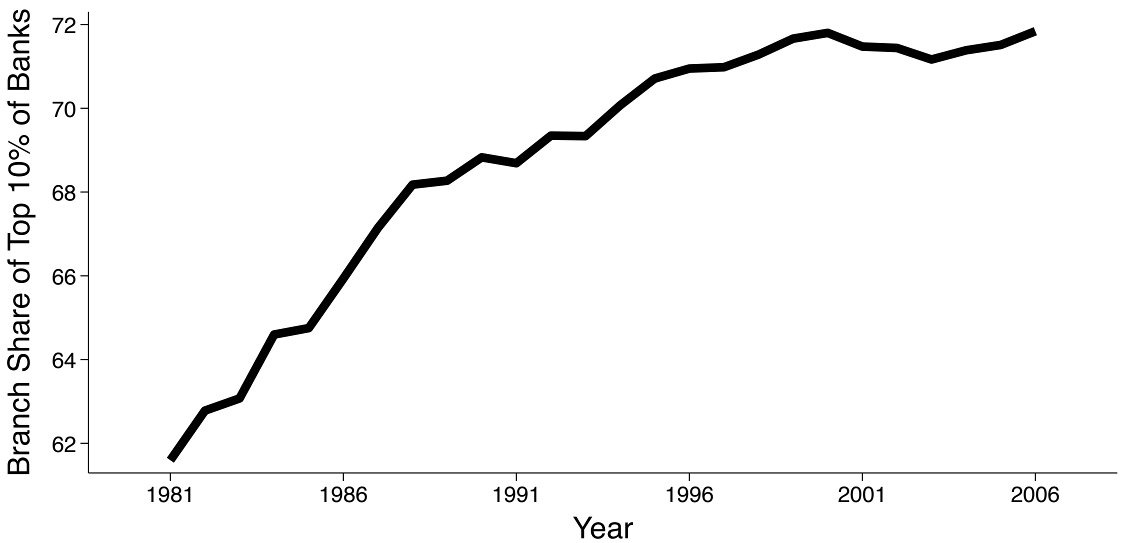
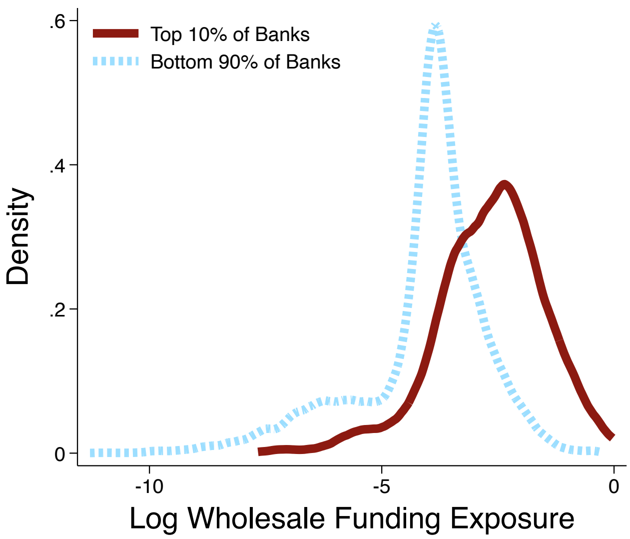
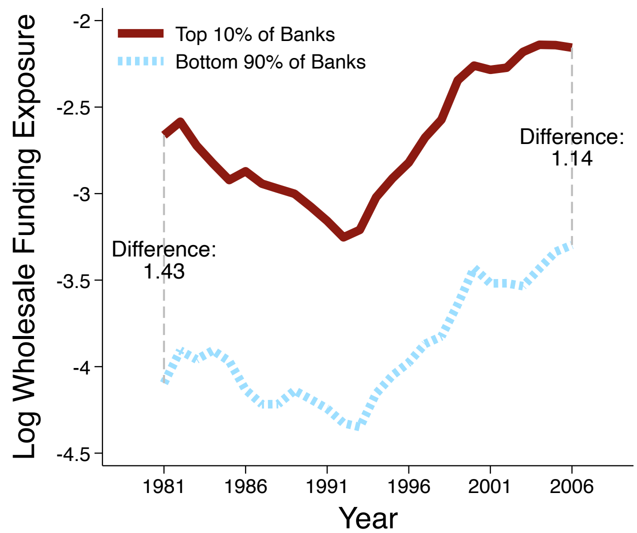


Figure 5: This figure shows branch ownership shares of the top 10% of banks by total deposits over time.



(a) Wholesale Funding Distribution in 1981



(b) Wholesale Funding Exposure Over Time

Figure 6: These figures display the use of wholesale funds across the bank size distribution. Panel (a) shows the distribution of log wholesale funding exposure across bank size bins in 1981. Panel (b) shows the average log wholesale funding exposure across bank size bins over time. Wholesale funding exposure is measured as the ratio of non-deposit liabilities to deposits. Bank size bins are the bottom 90% and the top 10% of banks by total deposits.

our sample. The difference between the groups was 1.43 log points in 1981 and declined to 1.14 log points by 2006, a 20% decline.

The implication is clear: in 1981, large banks used wholesale 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, which would be consistent with the decline in the relative use of wholesale funding by large banks.[26] Before embarking on this and other empirical investigations, we present our theory, which yields several empirical implications that guide the empirical analysis in Section 4.

3 A Spatial Theory of Banking

Consider an environment composed of banks and households that use banks for deposits and loans.[27] 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.

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_{jo}^D, and loans, r_{jo}^L.

In Appendix B.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 $o_{j\ell}^D \in O_j$ 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 $r_{j,o_{j\ell}^D}^D$ 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 $o_{j\ell}^L$ be the branch households in ℓ would choose if they choose bank j, and $r_{j,o_{j\ell}^L}^L$ the corresponding interest rate.

Given all banks' location choices and interest rate choices, the total demand for deposits and loans from

[26] While several factors can be attributed to the average increase in wholesale funding usage in the 1990s, such as looser monetary policy and growing competition from non-banks such as mutual funds, they do not directly explain the patterns in the cross-section of bank size.

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

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;[28] 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, 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.[29]

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

[28] 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).

[29] We provide evidence that bank appeal declines with distance from a bank's headquarters in Appendix C.2.

must pay a local fixed cost, Ψ_o.

Additionally, to operate $N_j \equiv |O_j|$ branches and choose common components of bank appeal for both of its services, $\bar{Q}_j^D$ and $\bar{Q}_j^L$, the bank must hire $\mathcal{C}(N_j, \bar{Q}_j^D, \bar{Q}_j^L)$ workers in its headquarters location, with $\mathcal{C}$ twice continuously differentiable, strictly increasing, and strictly convex in its second and third arguments. We further assume that, for any weakly positive N, $\bar{Q}^D$, and $\bar{Q}^L$, $\mathcal{C}_D(N, 0, \bar{Q}^L) = \mathcal{C}_L(N, \bar{Q}^D, 0) = 0$ and $\lim_{t\to\infty} \mathcal{C}_D(N, t\bar{Q}^D, t\bar{Q}^L) + \mathcal{C}_L(N, t\bar{Q}^D, t\bar{Q}^L) = \infty$, where $\mathcal{C}_D$ and $\mathcal{C}_L$ denote the partial derivatives with respect to its second and third arguments respectively. Finally, we assume that $\mathcal{C}$ can be expressed as $\mathcal{C}(N, \bar{Q}^D, \bar{Q}^L) = C\left(H^D(N)\bar{Q}^D, H^L(N)\bar{Q}^L\right)$, with H^D and H^L strictly increasing and weakly log convex, and C homothetic in its two arguments. Hence, we model the span-of-control costs of the bank through the cost of increasing the bank's appeal. Namely, investments in bank appeal are more costly, and increasingly so, when the bank operates more branches.[30]

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 $W_j = L_j - D_j$. If the bank gets funds through the wholesale market, it pays a higher interest rate on those funds than for retail deposits. 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, 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).[31]

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

[30] Kleinman (2023) studies the role of headquarter-level investments in service firms' spatial expansion.

[31] This wholesale fund cost function can be justified as a violation of the Modigliani-Miller theorem that results from debt overhang costs as in (Andersen et al., 2019), with deposits being senior to wholesale funding liabilities (or as in the classic adverse selection model in Stein (1998)) It can also be understood as different banks operating in segmented wholesale markets depending on the characteristics and actions that lead to their wholesale funding exposure. Specific government policies that favor banks with lower wholesale funding exposure could generate it too. In any case, the bank takes it as given, and so does our equilibrium analysis. A full micro-foundation requires modeling the entire wholesale fund market, which falls beyond the scope of this paper.

thus given by

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

subject to (2), (3), (4), (5), (6), (7), $W_j = L_j - D_j$, $N_j = |O_j|$, 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.[32] We relegate the proof of this result to Appendix A.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 bank j's problem as

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

subject to

$$\begin{aligned} D_j &\geq \int T^D \left(\delta_{o^D_{j\ell}, \ell}\right) Q^D_{j\ell} A^D_\ell \mathcal{D}\left(r^D_j\right) d\ell, \\ L_j &\leq \int T^L \left(\delta_{o^L_{j\ell}, \ell}\right) Q^L_{j\ell} A^L_\ell \mathcal{L}\left(r^L_j\right) d\ell, \end{aligned}$$

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

Note that, since banks set the same interest across all branches, the profits of the bank 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 these constraints are and, therefore, overall profits.

[32] This is consistent with Radecki (1998), Heitfield (1999), Heitfield and Prager (2004), Biehl (2002), Park and Pennacchi (2008), Yankov (2024), Granja and Paixao (2023), and Begenau and Stafford (2022), who find that banks predominantly set uniform rates across branches.

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 B.2, 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.[33] In this limiting case, it will be optimal for the bank to set up many plants. As we showed in Oberfield et al. (2024), this implies that the bank'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 bank's problem is then given by

$$\pi_j = \sup_{\substack{\omega_j, D_j, L_j, N_j, \bar{Q}_j^D, \bar{Q}_j^L, \\ r_j^D, r_j^L, \{n_{j\ell}\}_\ell}} \left(r_j^L - \theta_j^L\right) L_j - \left(r_j^D + \theta_j^D\right) D_j - \int \psi_\ell n_{j\ell} d\ell - R(\omega_j)\omega_j D_j - w_j^* \mathcal{C}(N_j, \bar{Q}_j^D, \bar{Q}_j^L)$$

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

$$D_j \geq \int Q_{j\ell}^D A_\ell^D \kappa^D(n_{j\ell}) \mathcal{D}\left(r_j^D\right) d\ell, \tag{9}$$

$$L_j \leq \int Q_{j\ell}^L A_\ell^L \kappa^L(n_{j\ell}) \mathcal{L}\left(r_j^L\right) d\ell, \tag{10}$$

and, abusing notation slightly, $N_j \equiv \int n_{j\ell} d\ell$. $\kappa^D(n)$ 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 B.2. 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 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

[33] 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 costs are $H^D(|O|;\Delta) = h^D(\Delta^2|O|)$ and $H^L(|O|;\Delta) = h^L(\Delta^2|O|)$; the local fixed cost is $\Psi_\ell(\Delta) = \Delta^2\psi_\ell$.

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

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.[34] As a result, higher wholesale funding ω_j

[34]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

leads to higher r_j^L and r_j^D, and hence higher $\mathcal{D}(r_j^D)$ and lower $\mathcal{L}(r_j^L)$.[35] 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,

$$\lambda_j^D Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_j^D\right) \kappa^{D'}(n_{j\ell}) + \lambda_j^L Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_j^L\right) \kappa^{L'}(n_{j\ell}) = \psi_\ell + w_j^* \mathcal{C}_N(N_j, \bar{Q}_j^D, \bar{Q}_j^L),$$

   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 reliance and bank appeal, namely,

$$\omega_j = \frac{L_j - D_j}{D_j},$$

$$w_j^* \mathcal{C}_D(N_j, \bar{Q}_j^D, \bar{Q}_j^L) = \int \lambda_j^D A_\ell^D \mathcal{D}(r_j^D) \kappa^D(n_{j\ell}) J_{j\ell}^D \phi_{j\ell} d\ell,$$

$$w_j^* \mathcal{C}_L(N_j, \bar{Q}_j^D, \bar{Q}_j^L) = \int \lambda_j^L A_\ell^L \mathcal{L}(r_j^L) \kappa^L(n_{j\ell}) J_{j\ell}^L \phi_{j\ell} d\ell.$$

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.

[35] 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.

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 Banks' 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 $Q^D_{j\ell}$ and $Q^L_{j\ell}$, 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 $z^D_j \equiv \lambda^D_j \bar{Q}^D_j \mathcal{D}(r^D_j)$ and $z^L_j \equiv \lambda^L_j \bar{Q}^L_j \mathcal{L}(r^L_j)$. In addition, define $\sigma_j \equiv w^*_j \mathcal{C}_N(N_j, \bar{Q}^D_j, \bar{Q}^L_j)$ 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 density of branches of bank j in location ℓ) is given by

$$\left[z^D_j J^D_{j\ell} A^D_\ell \kappa^{D\prime}(n_{j\ell}) + z^L_j J^L_{j\ell} A^L_\ell \kappa^{L\prime}(n_{j\ell})\right] \phi_{j\ell} = \psi_\ell + \sigma_j. \tag{15}$$

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^D_j and λ^L_j which determine z^D_j and z^L_j) 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 costs $h^D(\cdot)$ and $h^L(\cdot)$ are increasing and log convex. This then leads to "span-of control" sorting as we show in the next lemma and proposition.

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 that their relative span of control costs is larger than their relative deposit and loan productivities. All proofs are relegated to Appendix A.

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 $\sigma_2/\sigma_1 > z_2^D/z_1^D = z_2^L/z_1^L$.*

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 services so $z_2^D/z_1^D = z_2^L/z_1^L > 1$. Among locations with the same deposit abundance $\alpha_\ell \equiv A_\ell^D/A_\ell^L$, 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 bank productivities across services, $z_2^D/z_1^D = z_2^L/z_1^L$, or deposit abundance, 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 bank 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 bank 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. 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. Banks 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 deposit abundance 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.

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 abundance, 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 bank'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,

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

Proposition 6 *Suppose that* $d \log B_j^D = d \log B_j^L \equiv d \log B$. *Then, holding fixed the bank's branch locations,* n_j,

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

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 $\varepsilon_j^{\mathcal{C}}$ 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 $\varepsilon_j^{\mathcal{C}}$ 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.[36] 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.

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-abundant locations versus locations with more lending opportunities?

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.[37]

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, $\varepsilon_j^\lambda > 0$.

[36] In Appendix C.3 we show that banks that entered with headquarters in high-density counties grew more than banks headquartered in low-density counties.

[37] 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.

Finally, the elasticity of complementarity of the cost of appeal, given by

$$\chi_j = \frac{d \log \mathcal{C}_D/\mathcal{C}_L}{d \log \bar{Q}^D/\bar{Q}^L},$$

where $\mathcal{C}_D$ and $\mathcal{C}_L$ denote the derivatives of $\mathcal{C}(\cdot)$ with respect to its second and third arguments, respectively, and the derivative is taken holding fixed the first argument.. Since $\mathcal{C}(\cdot)$ is convex in its second and third arguments, $\chi_j \geq 0$.[38]

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, holding fixed the bank's branch locations, n_j,*

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

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 $\mathcal{C}(N, \bar{Q}_j^D, \bar{Q}_j^L) = \tilde{\mathcal{C}}(N, \max\{\bar{Q}_j^D, \bar{Q}_j^L\})$, which implies both 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.[39]

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

[39] 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).

An implication of the dominance of mismatch sorting when these elasticities are sufficiently large is that, all else equal, banks headquartered in locations that have more lending opportunities are more likely to expand to deposit-abundant locations than banks headquartered in deposit-abundant 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 Span-of-Control Sorting

We begin by exploring how different banks set up branches across US counties. In Figure 7, we consider branching patterns in 1981 and 2006, the beginning and end of our sample. We split banks into three size groups: the bottom 50% of banks, the 50th-90th percentile of banks, and the top 10% of banks by total deposits. We study the distribution of branches within each size group across four population density groups: the bottom 50%, 50th-75th percentile, 75th-95th percentile, and 95th-100th percentile. Span-of-control sorting then implies, since dense locations also have high rents and, more generally, high fixed costs of setting up branches, that smaller size groups would locate disproportionately in the least dense counties, while the larger size groups would locate disproportionately in the most dense counties (Proposition 4).

Figure 7 confirms the existence of this form of spatial sorting. In 1981, 44% of branches of the smallest banks could be found in counties in the bottom half of the population density distribution. Only 8% of their branches could be found in the top 5% of population-dense counties. In contrast, only 6% of the largest banks' branches could be found in the low-density counties, while 48% of their branches could be found in the counties with the highest density. The intermediate size group's branches are more evenly spread out in terms of county density.

The largest banks experienced a shift in their branching patterns by 2006. The top 10% of banks reduced their share of branches in the densest 5% of counties by about 8 percentage points, while the share of their branches in the bottom 50%, 50-75th percentile, and 75-95th percentile of counties increased by 1.1pp, 2pp, and 4.5pp, respectively. Changes in the other two groups are less pronounced. The intermediate bank size group also increased their share of branches in the bottom 50% of counties, although the decline in the high-density counties was more spread out. The smallest 50% of the banks tended to spread geographically, with slightly more presence in the densest and least-dense counties. Thus, sorting weakened between 1981 and 2006. The change was largely driven by the largest banks increasing their branch share in counties with densities below the top 5%. If large banks are more productive, and if dense counties exhibit higher branching costs, then the patterns displayed in Figure 7 specifically suggest a decline in span-of-control sorting.

We now turn to a more rigorous study of the importance of span-of-control sorting and its decline over time. The purpose of this exercise is to explore whether banks that were initially productive, and therefore large, were relatively more present in the densest locations and gradually expanded into less dense counties.

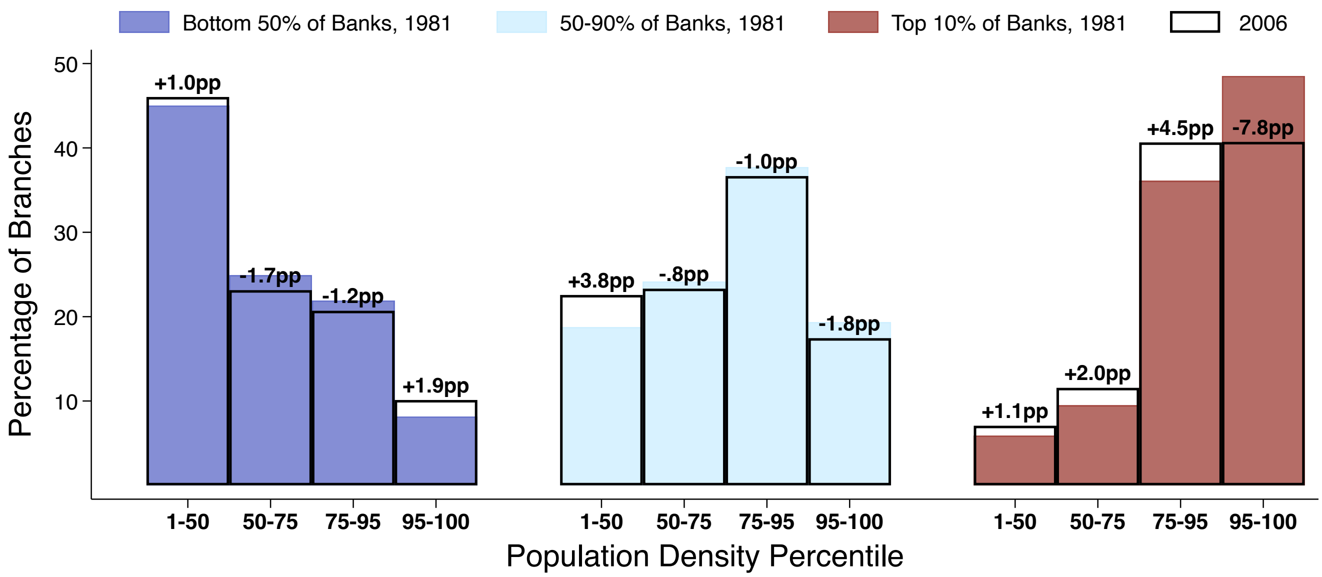


Figure 7: This figure shows the distribution of bank branches across population density bins and across bank size bins. Bank size bins are the bottom 50%, the 50-90th percentile, and the top 10% of banks by total deposits. Density bins are the bottom 50%, the 50-75th percentile, the 75-95th percentile, and the top 5% of counties by population density. Colored bars represent branch distributions in 1981, while black unfilled bars represent branch distributions in 2006.

We measure sorting patterns using a regression given by

$$\log \text{Density}_{jst} = \beta_t \log \text{Dep/Branch}_{j0} + \text{Fixed Effects} + \varepsilon_{jst}, \qquad t = 1981, \ldots, 2006 \tag{16}$$

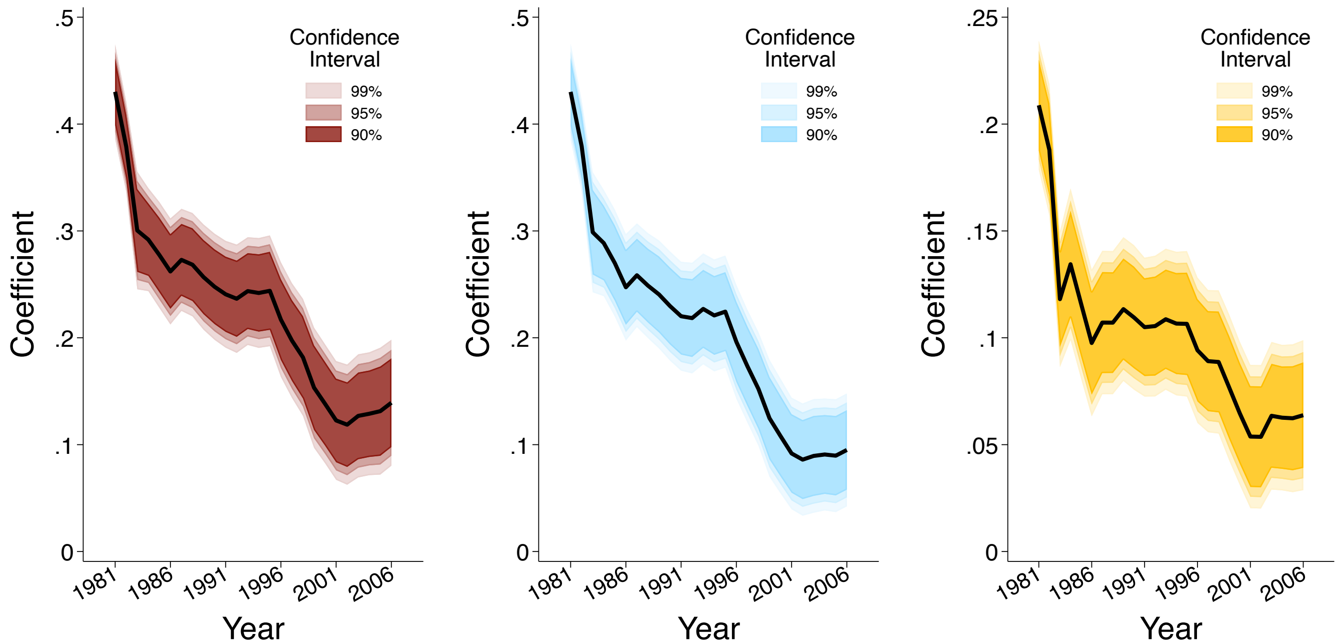
where, for each bank j branching in state s at time t, their branch density is defined as

$$\log \text{Density}_{jst} = \sum_{c \in s} \text{BranchShare}_{jct} \times \log \text{Density}_{ct}.$$

Here, BranchShare_{jct} is bank j's share of branches in county c relative to their total number of branches in state s at time t and $\log \text{Density}_{ct}$ is the log of the population density of county c at time t. We use deposits per branch of bank j, $\text{Deposits/Branch}_{j0}$ to proxy for bank j's productivity in the first year they enter the sample. All results are similar if we use total deposits instead of deposits per branch to proxy for a bank's productivity.[40]

We consider increasingly restrictive fixed effects in our specification. First, we use state × year fixed

[40] Note that deposits per branch is strongly correlated with bank size, which we document in Figure C.1 the Appendix. To verify that our results are robust to the choice of productivity proxy, we also conduct our analysis using bank j's initial size, measured as the log of their total deposits, in Figure C.2 in the Appendix.



(a) State × Year FE (b) State × HQ State × Year FE (c) State × HQ CZ × Year FE

Figure 8: This figure reports the yearly regression coefficients for equation (16). Panel (a) uses state-by-year fixed effects, panel (b) uses state-by-headquarter state-by-year fixed effects, and panel (c) uses state-by-headquarter commuting zone-by-year fixed effects. Standard errors are clustered at the bank level.

effects to explore sorting patterns within a state at a point in time. Next, we use state × headquarter state × year fixed effects to account for out-of-state branching effects. Finally, we use state × headquarter state × headquarter commuting zone × year fixed effects, which effectively assess sorting among banks headquartered in the same commuting zone (e.g. San Francisco) that have branches in a given target state (e.g. Oregon) in a given year (e.g. 1993). This specification is the most consistent with our theory, which predicts span-of-control sorting holding fixed the headquarter location of each bank.

A positive β_t coefficient is consistent with span-of-control sorting. It implies that, when banks expand into a new state, high-productivity banks locate in denser areas, while less productive banks locate in low-density areas.[41] The value of β_t measures the magnitude of spatial sorting. We report the results graphically in Figure 8. Panel (a) reports the results for state × year fixed effects, panel (b) reports the results for state × headquarter state × year fixed effects, and panel (c) reports the results for state × headquarter state × headquarter commuting zone × year fixed effects. We report each estimate $\widehat{\beta}_t$ along with its 90%, 95%, and 99% confidence intervals. Standard errors are clustered at the bank level.

Two results emerge. First, the estimated coefficient $\widehat{\beta}_t$ is positive and significant at the 1% level for each

[41] Note that, in standard heterogeneous firm models, more productive firms serve all the markets that low productivity firms serve, and more. Namely, in those models, the marginal low-density markets are not served by the less productive firms. Hence, those models predict a negative β_t.

time period and each specification, providing support for the existence of span-of-control sorting. The last two specifications in particular alleviate concerns that sorting patterns are driven by headquarters choice, since we are comparing sorting in a target state among firms with the same headquarter location. We also conducted a pooled analysis consisting only of out-of-state banks to further confirm the existence of span-of-control sorting in Table C.1 in the Appendix.

Second, there is a stark decline in $\widehat{\beta}_t$ over time for all specifications. The magnitudes are large. In 1981, a 10% increase in the deposits per branch of a bank would imply a 2.1-4.3% increase in the branch-weighted population density of their active counties. By 2006, the same increase in deposits per branch would imply a 0.6-1.4% increase in the branch-weighted population density — a decline of approximately two-thirds. Given the patterns in the raw data shown in Figure 7, we interpret this result to imply that large banks expanded heavily into lower-density counties over time.

4.2 Connecting Mismatch Sorting to the Decline in Span-of-Control Sorting

Why did span-of-control sorting decline over time? Our theory naturally rationalizes these patterns. Span-of-control sorting implies that large banks are located in denser locations while smaller banks are located in less dense areas. 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 geographic 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 what we have termed mismatch sorting: large banks expand to locations that reduce their reliance on wholesale funding. Since locations with large deposit abundance are less dense, the result is a reduction in span-of-control sorting.

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-abundant. 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-abundant locations. Namely, that deregulation motivated these banks to open relatively more branches in deposit-abundant 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, and that this effect was driven by banks with more exposure to wholesale funds and through their expansion into deposit-abundant counties. We present this evidence throughout the remainder of this section.

4.2.1 Dense Counties are More Loan Abundant

We start by providing evidence on the distribution of deposit abundance in space. We collect data on two sources of loans. First, 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.[42] These loans are reported at the census tract level, which we aggregate up to counties. The data are available starting in 1995. Second, we collect county-level mortgage loan volumes from the Home Mortgage Disclosure Act data (HMDA) starting in 1990.[43]

We measure deposit abundance (DepAbun_{ct}) as the ratio of total deposits to total originated loans within a county, namely,

$$\text{DepAbun}_{ct} = \frac{\text{Deposits}_{ct}}{\text{Mortgage Loan Volume}_{ct} + \text{CRA Small Business Loan Volume}_{ct}}. \tag{17}$$

The spatial mismatch sorting mechanism says that large banks expanded into deposit-abundant regions 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 the geographic deregulation that we documented above, we need to study how deposit abundance varies with county density. We document the relationship between population density and deposit abundance at the county level using the following county-level regression,

$$\log \text{DepAbun}_{ct} = \beta \log \text{Density}_{ct} + \boldsymbol{\gamma}'\mathbf{X}_{ct} + \gamma_{st} + \varepsilon_{ct}. \tag{18}$$

We report the results in the form of a binscatter plot in Figure 9. Panel (a) uses our preferred measure of loans that combines mortgages and CRA loans, while panel (b) only uses mortgage loans. Regardless of the measure, we find a strong and significant negative correlation between deposit abundance and population density. This holds with or without extensive demographic controls and state × year fixed effects. We report regression results in Table C.2 in the Appendix and document that the relationship is highly significant across specifications.

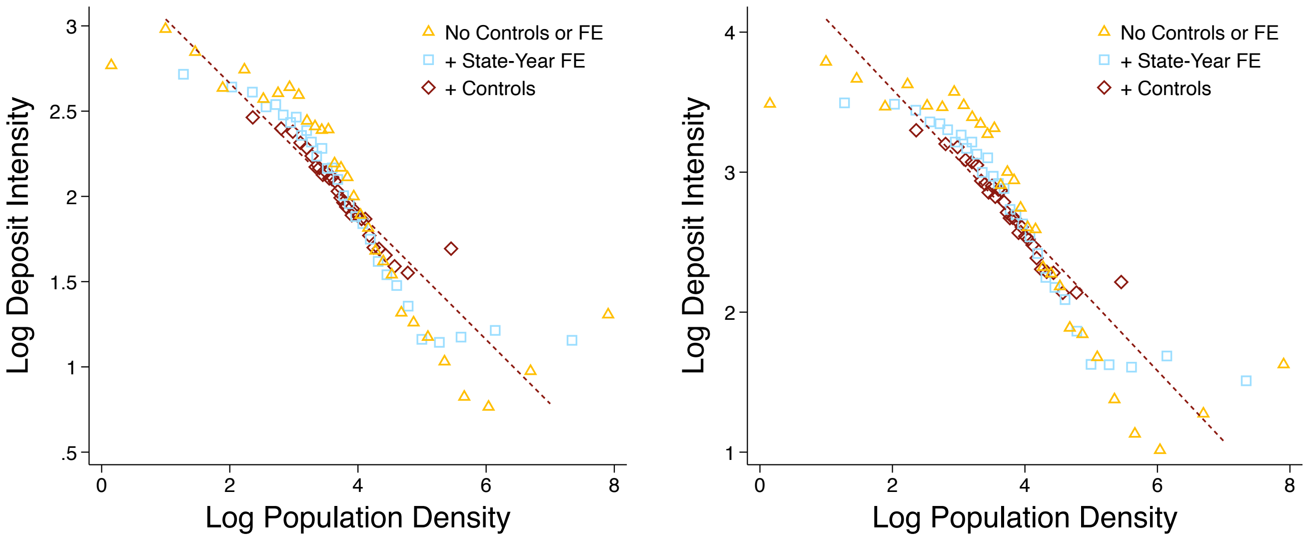
4.2.2 Banks with Loan Abundant Headquarters Use More Wholesale Funding Ex-Ante

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

$$\log \text{WFE}_{j,1981} = \beta \log \text{DepAbun}_{c_j^{HQ},1981} + \boldsymbol{\gamma}_c'\mathbf{X}_{c,1981} + \boldsymbol{\delta}_j'\mathbf{X}_{j,1981} + \text{Fixed Effects} + \varepsilon_j, \tag{19}$$

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

[43] For years that are missing from our primary sample, we backfill the loan data. Since our analysis draws heavily on cross-sectional variation across counties rather than across time, we are not particularly concerned with measurement error. Nevertheless, we conduct several of our analyses using data from 1990-2006 to ensure that our results are robust to excluding the back-filled years. We also show in Appendix Figure C.3 that the autocorrelation in our deposit abundance measure is above 0.7 even with a five-year lag, which further validates our measure.



(a) Mortgages + CRA Loans

(b) Mortgage Loans Only

Figure 9: This figure reports results for regression equation (18) in the form of binscatters. Panel (a) uses our preferred measure of loans that combines mortgages and CRA loans, while panel (b) only uses mortgage loans. In each plot, the yellow triangles consider the raw relationship between deposit abundance and population density, the blue squares add in state × year fixed effects to control for institutional and fundamental differences across states, and the red diamonds add in demographic controls such as income as well as age and race demographics. The fitted red line reflects the linear relationship implied by the third specification.

where $\log \text{WFE}_{j,1981}$ denotes the log of bank j's wholesale funding exposure in 1981 and $\log \text{DepAbun}_{c_j^{HQ},1981}$ is a measure of deposits to loans for bank j's headquarter county. We gradually add controls for the density of a bank's headquarters county and the size and deposits per branch of the bank, as well as a headquarter state fixed effect. We present the results in Table I.

We find that banks use less wholesale funding when they are headquartered in locations that are deposit-abundant. Columns (1) and (4) only consider the relationship between wholesale funding exposure and deposit abundance. 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. In addition, 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. We also include the bank's size as a control in case large banks have better access to wholesale funds. Columns (3) and (6) include headquarter state fixed effects, which absorb differences in state-level characteristics such as differences in regulation. Consistent with mismatch sorting, even with all these controls, the coefficient on deposit abundance remains negative and significant.

	Dependent Variable: $\log \text{WFE}_{j0}$					
	Mortgages + CRA Loans			Mortgages Loans Only		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \text{DepAbun}_{c_j^{HQ}0}$	−0.238***	−0.112***	−0.053**	−0.126***	−0.042***	−0.022**
	(0.019)	(0.018)	(0.022)	(0.009)	(0.009)	(0.011)
$\log \text{Density}_{c_j^{HQ}0}$		0.074***	0.129***		0.078***	0.131***
		(0.016)	(0.019)		(0.015)	(0.019)
$\log \text{Deposits}_{j0}$		0.428***	0.491***		0.431***	0.491***
		(0.019)	(0.025)		(0.019)	(0.025)
$\log \text{Dep/Branch}_{j0}$		0.027	−0.027		0.016	−0.028
		(0.024)	(0.035)		(0.024)	(0.035)
HQ State FE			✓			✓
Observations	9614	9611	9611	9647	9613	9613
R^2	0.04	0.20	0.25	0.04	0.20	0.25

Table I: This table reports the results of regression equation (19). The dependent variable is log wholesale funding exposure in the first year bank j appears in our sample. Independent variables are the log of bank j's headquarter county deposit abundance, the log of bank j's headquarter county population density, bank j's log deposits, and bank j's log deposits per branch, all measured in the first year bank j appears in our sample. Standard errors are reported in parentheses and are clustered at the headquarter county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

4.2.3 High Wholesale Funding Banks Expand Into Deposit Abundant Counties

The previous two sections provide a motive for our mismatch sorting theory: banks that were limited to lending opportunities in or near their headquarter county prior to deregulation had an incentive to expand into deposit-abundant locations post-deregulation to ameliorate their use of wholesale funds. However, identifying this sorting mechanism empirically is challenging because our theory only implies sorting through one mechanism after holding fixed the others. In particular, Proposition 4 implies that high-productivity banks sort into high-cost locations, but only after conditioning on banks' distance from headquarters and wholesale funding exposure, and only after holding fixed the deposit abundance of the locations in question. Similarly, Proposition 5 implies that banks with higher exposure to wholesale funding sort into deposit-abundant locations, conditional on bank productivity and size as well as the fixed cost of operating a branch across locations. Therefore, an ideal empirical strategy should control for one form of sorting while allowing the other to vary.

We therefore leverage the staggered and bilateral nature of the geographic deregulation episodes throughout the 1980s and 90s to assess the importance of span-of-control and mismatch sorting. Our methodology is designed to control for one type of sorting while allowing the other to vary. For example, compare banks that are headquartered in a given location, e.g. San Francisco, that have similar wholesale funding exposure prior to expansion but have variation in their deposits per branch (our proxy for bank productivity). When these banks expand into a newly opened state, e.g. Oregon, we only look within counties that had similar deposit abundance prior to the opening event but have variation in their population density (our proxy for branching costs). If we find that the banks with higher deposits per branch are relatively more active in the high-density counties, this constitutes evidence of span-of-control sorting.

Of course, since there could be many other reasons why banks expand into specific locations. Hence, we also need to control for bank- and county-specific effects to isolate the effect of sorting. We measure span-of-control sorting using the Poisson regression,

$$\log(\mathbb{E}[\text{Branches}_{jct}]) = \beta_{\text{SOC}} \log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch} + \gamma \log \text{Distance}_{jc} + \delta_{jst} + \delta_{cht} + \delta_{s,cz,t,\text{WFE}^{10}_{js},\text{DepAbun}^{10}_{ch}} + \varepsilon_{jct}. \quad (20)$$

Here, Dep/Branch_{js} is the deposits per branch of bank j in the year before bank j's headquarter state was permitted to expand into state s, and Density_{ch} is the density of county c in the year before county c's state became open to banks from headquarter state h. A positive estimate of β_{SOC} indicates that banks with higher deposits per branch place relatively more branches in high-density counties on average, which we interpret as span-of-control sorting.

As discussed, we control for several potential concerns with our specification using a host of fixed effects. δ_{jst} is a bank × state × year fixed effect, which absorbs unobservable characteristics between bank j and state s in each year. For example, if high productivity bank j prefers to lend to manufacturing firms, and firms in low density locations in state s tend to be biased toward manufacturing, bank j may choose to locate their branches in a way that appears to violate span-of-control sorting; this fixed effect controls for such a force. Second, δ_{cht} is a county × headquarter state × year fixed effect, which absorbs unobservable characteristics between county c and headquarter state h. For example, if county c is part of a metropolitan area that crosses over into state h, it may receive preferential treatment among banks headquartered in state h, irrespective of its fundamentals.

Finally, central to our analysis is the last fixed effect, $\delta_{s,cz,t,\text{WFE}^{10}_{js},\text{DepAbun}^{10}_{ch}}$, which is a target state × headquarter commuting zone × year × bank wholesale funding exposure decile × county deposit abundance decile fixed effect.[44] This fixed effect implies that we estimate the coefficient of interest from variation across banks with similar wholesale funding exposure in the same headquarter commuting zone that expand into

[44] We use commuting zones rather than counties to increase power. When commuting zones extend across state boundaries, we split the commuting zone into two regions and only consider the banks within the commuting zone-headquarter state pair.

counties with similar deposit abundance in the same state in the same year.[45] This allows us to interpret β_{SOC} as a measure of span-of-control sorting consistent with Proposition 4.

We conduct a similar exercise to test for the presence of mismatch sorting. Our specification for this test is

$$\log(\mathbb{E}[\text{Branches}_{jct}]) = \beta_{\text{MM}} \log \text{WFE}_{js} \times \log \text{DepAbun}_{ch} + \gamma \log \text{Distance}_{jc} + \delta_{jst} + \delta_{cht} + \delta_{s,cz,t,\text{Dep/Branch}^{10}_{js},\text{Density}^{10}_{ch}} + \varepsilon_{jct}. \quad (21)$$

The interpretations of the variables and the fixed effects are analogous to the span-of-control sorting from above. An estimate of $\beta_{\text{MM}} > 0$ implies that banks with higher wholesale funding exposure tend to place more branches in relatively deposit-abundant locations, conditional on span-of-control sorting.[46] This is precisely the mismatch sorting channel we describe in Proposition 5.

The stacked nature of (20) and (21) allows banks and locations to change categories across events, which is another benefit of our approach. For example, a bank that starts in the 8th deposits-per-branch decile before expansion and ends in the 9th decile will now be compared to other 9th decile banks in subsequent opening events. To keep the focus on bank characteristics around the expansion period, we limit the time frame after a bilateral opening event to 5 years post-opening. We explore the longer-term effects by looking at the 6-10 year windows in Table C.13 in the Appendix, which we discuss at the end of this section.

While our approach to measuring the types of sorting is fairly saturated, one concern is that the granular fixed effects require us to restrict our analyses to states that have more than 10 counties. Additionally, restricting the analysis to banks headquartered in the same commuting zone with similar characteristics reduces the number of banks we include in our analysis. To ensure that our estimates are robust to these concerns, we estimate a third specification that linearly accounts for both sorting forces simultaneously, namely,

$$\log(\mathbb{E}[\text{Branches}_{jct}]) = \beta_{\text{SOC}} \log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch} + \beta_{\text{MM}} \log \text{WFE}_{js} \times \log \text{DepAbun}_{ch} + \gamma \log \text{Distance}_{jc} + \delta_{jst} + \delta_{cht} + \delta_{s,cz,t} + \varepsilon_{jct}. \quad (22)$$

We report our results for specifications (20)-(22) in Table II. Column (1) reports the results for specification (20), column (2) reports the results for specification (21), column (3) reports the results for specification (22), and column (4) repeats column (3) but adds in $\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$ and $\log \text{WFE}_{js} \times \log \text{Density}_{ch}$ terms to ensure that the results in column (3) are not driven by variation not related to our two sorting forces. We find evidence for both span-of-control sorting and mismatch sorting across all

[45] Note that there are some cases where a bank holding company's headquarter location is not the same as its member banks. Given the importance of comparing banks in the same location, we remove these banks, as well as banks whose headquarter location changes during the sample, for this portion of our analysis.

[46] Technically, Proposition 4 conditions on bank productivity as well as bank size in order to control for span-of-control costs. We estimate specification (21) with an additional size decile fixed effect in Table C.10 and find similar results.

Dependent Variable: Number of Branches				
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.414***		0.532***	0.349***
	(0.136)		(0.078)	(0.096)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.235**	0.144**	0.267***
		(0.103)	(0.061)	(0.080)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.410**
				(0.162)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.068*
				(0.041)
$\log \text{Distance}_{jc}$	−0.781**	−1.203***	−1.318***	−1.332***
	(0.359)	(0.299)	(0.265)	(0.268)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
. . . × WFE Decile × DepAbun Decile FE	✓			
. . . × Dep/Branch Decile × Density Decile FE		✓		
Obs.	5629	5172	10647	10647
Pseudo-R^2	0.65	0.65	0.70	0.70

Table II: This table reports the results of regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

specifications. The estimated coefficients are consistently significant at the 5% level, and are often significant at the 1% level. Additionally, we estimate a negative coefficient on distance from headquarters, which is also consistent with our theory.

We conduct several robustness tests to validate our findings. We begin by addressing potential problems with sample selection. First, as we discuss in Section 2, we drop banks whose total deposits are less than half their liabilities to avoid banks with unorthodox business models, accounting for approximately 3% of bank-year observations. Table C.5 shows that adding them back in does not change the results.

Second, in Section 2 we highlight that some banks were grandfathered into the Bank Holding Company Act of 1956, implying that some out-of-state branching existed prior to the deregulation of the 1980s and 90s. Although these branches are important when accounting for bank-level decisions, they may interfere with our empirical estimates. We therefore repeat our analysis using only branches that banks open after a bilateral opening event. Table C.6 shows that only considering these branches does not change the results, and that their statistical significance is enhanced further.

Third, we address potential concerns that our results reflect measurement error due to the back-filling of our loan-level data. We present results in which the sample is truncated in 1990 in Table C.7. We find significant estimates for both sorting forces across all specifications, suggesting that our results are not driven by this type of measurement error.

We then consider how our choice of covariates affects the results. We conduct our analysis using mortgage loans instead of total loans (Table C.8), total deposits instead of deposits per branch (Table C.9), and banks' initial deposits per branch instead of their deposits per branch in the year prior to a bilateral opening event (Table C.11). Of the 9 additional estimates per sorting force, only 1 becomes insignificant for mismatch sorting (column (2) in Table C.8) and only 2 become insignificant for span-of-control sorting (columns (1) and (4) in Table C.9). Nevertheless, the point estimates retain the correct sign in all specifications.[47]

Banks that are more exposed to wholesale funding prior to an opening event are more likely to open new branches in deposit-abundant counties, as we showed above. Once they do so, their reliance on wholesale funding should decrease, and their subsequent expansion should be into higher-density counties with more lending opportunities. Hence, in Table C.12, we also explore how our estimates change when we allow for bank variables to change over time rather than holding them fixed at their pre-opening levels. Although our model is static, the results are consistent with this interpretation.[48]

In the next section, we study whether a bank's spatial expansion, and particularly expansion into deposit-abundant counties, is associated with a decline in wholesale funding exposure, as our theory suggests.

4.2.4 The Impact of Geographic Expansion on Relative Wholesale Funding Exposure

We have shown that banks with high wholesale funding exposure will open branches in deposit-abundant counties when given the chance. We now provide further evidence for this channel by exploring the dynamics of their wholesale funding exposure following a geographic expansion. Our baseline specification takes the

[47] It is natural that these alternative measures are somewhat noisier, as the connection with the objects we intend to measure is looser than our baseline measures. For the loan variables, small business lending is more local than mortgage lending due to the importance of bank-firm relationships (Petersen and Rajan, 2002; Berger et al., 2005), and these loans are less likely to be securitized (Dou, 2021). As such, solely using mortgage loans instead of combined loans overestimates the relative demand for deposits to loans in a location. For bank productivity, deposits per branch and total deposits are both imperfect, but highly correlated, proxies of a bank's marginal costs of processing deposits and loans.

[48] All estimates are positive and significant except for the estimate of mismatch sorting in column (2). Although the insignificant estimate is positive, it suggests that the mismatch sorting force weakens over time since the estimate is only a third of the size of the estimate in column (2) in our baseline results. We test for this explicitly in Table C.13, where we estimate our main specifications (as in Table II) 6-10 years after each bilateral opening event rather than 0-5 years after. Although span-of-control sorting remains positive and significant, mismatch sorting weakens and becomes insignificant for all specifications.

form

$$\log \text{WFE}_{j,t+h} - \log \text{WFE}_{j,t-1} = \beta_h \mathbf{1}\{\Delta\text{Counties}_{jt} > 0\} + \boldsymbol{\gamma}_h' \mathbf{X}_{jt} + \delta_{th} + \delta_{jh} + \varepsilon_{jt}. \tag{23}$$

We include controls for log of bank j's total assets, the log of bank j's lagged deposits and non-deposit liabilities, the log change in bank j's number of branches, and three lags of the expansion indicator, $\mathbf{1}\{\Delta\text{Counties}_{jt} > 0\}$. A negative β_h coefficient implies that when bank j expands geographically between time $t+h$ and $t-1$, their wholesale funding exposure declines by approximately β relative to banks that did not expand. We consider five periods before and after the expansion at time t, $h = -5, \ldots, 5$.[49]

We then estimate how the effect of geographic expansion varies across banks with different levels of wholesale funding exposure. As we demonstrated in the previous section, banks that have a relatively high exposure to wholesale funding are more likely to expand into deposit-abundant locations. As such, we should expect these banks to experience larger declines in their wholesale funding exposure relative to low wholesale funding banks. We estimate this relative effect using the regression

$$\begin{aligned}\log \text{WFE}_{j,t+h} - \log \text{WFE}_{j,t-1} = \beta_h \mathbf{1}\{\Delta\text{Counties}_{jt} > 0\} + \beta_h^W \mathbf{1}\{\Delta\text{Counties}_{jt} > 0\} \times \text{HighWFE}_{jt-1} \\ + \boldsymbol{\gamma}_h' \mathbf{X}_{jt} + \delta_{th,\text{HighWFE}_{jt-1}} + \delta_{jh} + \varepsilon_{jt}.\end{aligned} \tag{24}$$

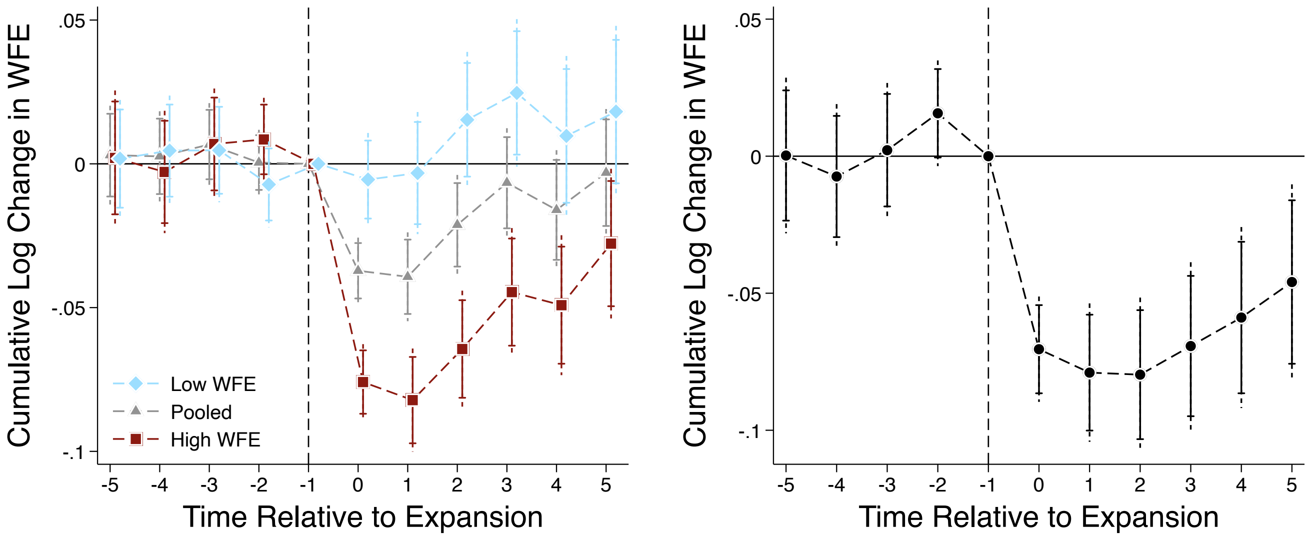
where HighWFE_{jt-1} is an indicator for whether bank j was in the top quartile of wholesale funding exposure at time $t-1$. We interact the time fixed effect with this indicator to absorb any level effects of banks that are heavy users of wholesale funds in the previous period. We present the results for specifications (23) and (24) in Figure 10.

We find that expansion is, on average, associated with a decline in wholesale funding exposure. Using the pooled specification (23), expansion leads to a cumulative decline of 4.5% in wholesale funding exposure in the first two years after expansion. The effect shrinks to about 2% in the following year, but remains significant. There are no statistically significant effects after the second year.

The pooled estimates mask substantial heterogeneity between low- and high-wholesale-funding-exposed banks. Splitting the sample by quartile, we find that the banks with the highest wholesale funding exposure experience an approximately 8-9% decline in their wholesale funding exposure after expansion. Unlike the pooled sample, these banks have significantly lower wholesale funding exposure for 5 years after expansion, although there is still some reversion toward zero. In contrast, the banks with the lowest wholesale funding exposure do not experience a decline in wholesale funding exposure, and even increase their wholesale funding slightly a few years after expansion. Pre-trends are close to zero and insignificant for both groups of banks.

Panel (b) plots the relative effect (β_h^W) for each time period. Consistent with the total effects in panel (a), we find a persistent relative negative effect on high wholesale funding banks. Again, there is no significant

[49] Due to the presence of substantial outliers in the dependent variable, we trim our dependent variable at the 1% and 99% level. These outliers are predominantly banks with wholesale funding exposures close to 0, which result in excessive growth rates.



(a) Total Effects

(b) Relative Effect of High WFE

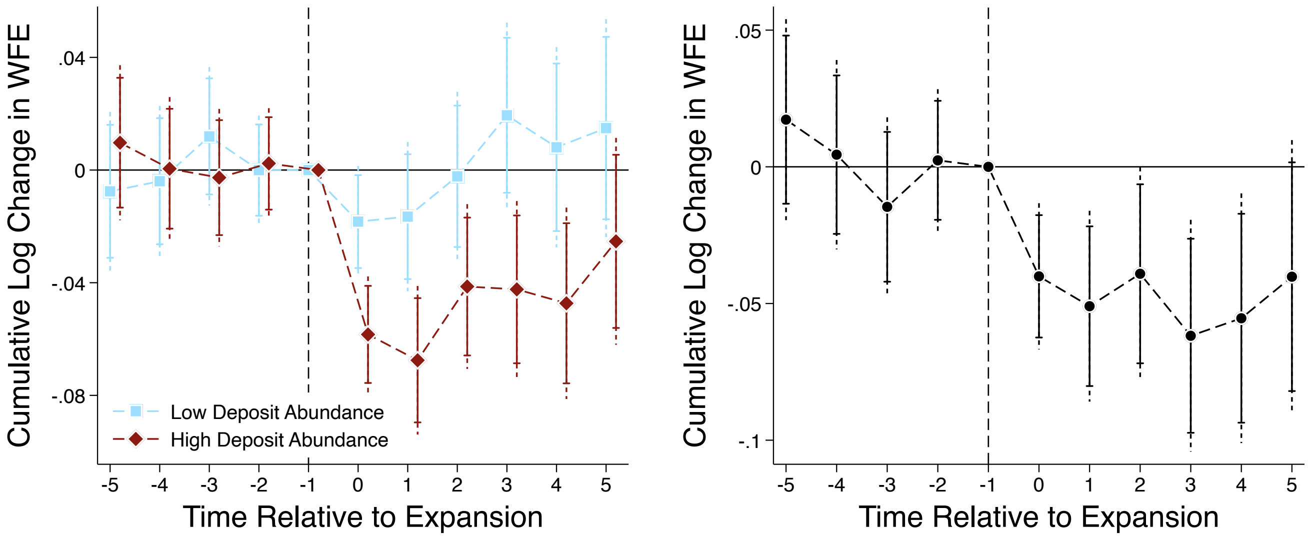
Figure 10: This figure plots the regression estimates for equations (23) and (24). Estimates are reported for time horizons $h = -5, \dots, 5$, with $h = -1$ normalized to 0. Panel (a) reports the level effects of geographic expansion relative to non-expanding banks for the pooled sample (gray), banks in the bottom three quartiles of wholesale funding exposure (blue), and banks in the top quartile of wholesale funding exposure (red). Panel (b) reports the relative effect between high and low wholesale funding exposure banks. Standard errors are adjusted for heteroscedasticity. 90% confidence intervals are reported as solid lines, while the 95% confidence intervals are reported as dotted lines.

pre-trend, suggesting that the change in wholesale funding exposure is due to the geographic expansion.

Our theory suggests that banks expand into high deposit abundance locations, which the previous section showed was done by banks with high levels of wholesale funding exposure, in order to reduce their reliance on wholesale funding. We now verify that banks that expand into counties that are deposit abundant experience a larger decline in their wholesale funding exposure than banks that expand into locations with relatively more lending opportunities. To test this, first define $\text{DepAbun}_{jt}^{\text{new}}$ to be the branch-weighted deposit abundance of the locations of bank j's new branches, conditional on expanding geographically at time t. Let also $\text{DepAbun}_{jt}^{\text{new},H}$ denote an indicator equal to 1 if new branch deposit abundance $\text{DepAbun}_{jt}^{\text{new}}$ is in the top quartile at time t, $\text{DepAbun}_{jt}^{\text{new},M}$ an indicator for new branch deposit abundance in the middle two quartiles, and $\text{DepAbun}_{jt}^{\text{new},L}$ an indicator for new branch deposit abundance in the bottom quartile. We use these indicators to estimate a third specification given by

$$\log \text{WFE}_{j,t+h} - \log \text{WFE}_{j,t-1} = \sum_{k \in \{L,M,H\}} \beta_h^k \mathbf{1}\{\Delta \text{Counties}_{jt} > 0 \text{ and } \text{DepAbun}_{jt}^{\text{new},k} = 1\}$$

$$+ \boldsymbol{\gamma}_h' \mathbf{X}_{jt} + \delta_{th,\text{HighWFE}_{jt-1}} + \delta_{jh} + \varepsilon_{jt}. \quad (25)$$



(a) Total Effect by New County Avg. Deposit Abundance (b) Relative Effect of High vs. Low Deposit Abundance

Figure 11: This figure plots the regression estimates for equation (24). Estimates are reported for time horizons $h = -5, \dots, 5$, with $h = -1$ normalized to 0. Panel (a) reports the level effects of geographic expansion relative to non-expanding banks for banks whose new counties' deposit abundance is in the bottom quartile among expanding banks (blue) and banks whose new counties' deposit abundance is in the top quartile among expanding banks (red). Panel (b) reports the relative effect between high and low deposit abundance expansion. Standard errors are adjusted for heteroscedasticity. 90% confidence intervals are reported as solid lines, while the 95% confidence intervals are reported as dotted lines.

We are interested in both the level effects of new branch low and high deposit abundance expansion, β_h^L and β_h^H, as well as the relative difference between the two. We plot the coefficients separately for $h = -5, \dots, 5$ in Figure 11a and the difference in the coefficients in Figure 11b.

We find that banks that expanded into the most deposit-abundant locations experienced a significant decline in wholesale funding exposure for the first four years after expansion. In contrast, banks that expanded into the least deposit-abundant locations do not exhibit significant changes in wholesale exposure. The difference in the two effects is significant at the 5% level for the first four years after expansion. Hence, banks with high wholesale funding usage reduced their exposure to wholesale funds upon expansion and (given the composition effects we identify in the previous section) do so by expanding into deposit-abundant locations. This is precisely the mismatch sorting force that emerges from our theory.

We explore the robustness of the results in this section among several dimensions. Given that we are most interested in the relative effects of wholesale funding exposure and deposit abundance, we report our robustness checks for the relative effects β_h^W and $\beta_h^H - \beta_h^L$. First, we vary our choice of expansion lags to ensure that our results are robust to model specification in Figure C.4. We find very few differences across our choices of lags. Second, in Figure C.5, we select on banks that never expand or only expand once to ensure that serial expansions are not driving our results. While these results are noisier due to a large reduction in sample size, we find broadly similar results. Third, in Figure C.6, we select on banks that expanded at some point in the sample — since expanding banks may be systematically different from non-expanding banks, this exercise rules out the possibility that bank-level differences are driving the effects. Again, our results remain consistent. We conclude that, indeed, banks with higher wholesale funding exposure and banks that expand into more deposit-abundant counties experience a large relative decline in their wholesale funding exposure.

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, generates this form 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 deposits 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 develop 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 study these issues quantitatively in future work. Our framework can also be readily used to study the effect of other deregulation episodes and proposals. One leading example is a deregulation of the European banking system that would allow banks to operate more freely across countries.

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Appendix

A Proofs

A.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

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

subject to

$$D_{j\ell} = T^D\left(\delta_{o_{j\ell}^D,\ell}\right) Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_{j\ell}^D\right) \quad (26)$$

$$L_{j\ell} = T^L\left(\delta_{o_{j\ell}^L,\ell}\right) Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_{j\ell}^L\right) \quad (27)$$

as well as (4), (5), (6), (7), $W_j = D_j - L_j$, and $N_j = |O_j|$. 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 Proof of Lemma 3

Proof. Toward a contradiction, suppose that $\sigma_2/z_2^D < \sigma_1/z_1^D$. 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 and $J_{2\ell}^L = J_{1\ell}^L$ and $J_{2\ell}^L = J_{1\ell}^L$, this inequality can only hold if $n_{2\ell} > n_{1\ell}$. Thus either $N_2 = N_1 = 0$ or $N_2 \geq N_1$. With this, we can derive a contradiction:

$$\begin{aligned}
\sigma_2 &= w_2^* \frac{dC\left(h^D(N_2)\bar{Q}_2^D, h^L(N_2)\bar{Q}_2^L\right)}{dN_2} \\
&= w_2^* \left[h^{D\prime}(N_2)\bar{Q}_2^D C_D\left(h^D(N_2)\bar{Q}_2^D, h^L(N_2)\bar{Q}_2^L\right) + h^{L\prime}(N_2)\bar{Q}_2^L C_L\left(h^D(N_2)\bar{Q}_2^D, h^L(N_2)\bar{Q}_2^L\right)\right] \\
&= w_2^* \int \left[\frac{h^{D\prime}(N_2)}{h^D(N_2)} z_2^D J_{2\ell}^D A_\ell^D \kappa^D(n_{2\ell}) + \frac{h^{L\prime}(N_2)}{h^L(N_2)} z_2^L J_{2\ell}^L A_\ell^L \kappa^L(n_{2\ell})\right] \phi_{2\ell} d\ell \\
&\geq w_2^* \int \left[\frac{h^{D\prime}(N_1)}{h^D(N_1)} z_2^D J_{2\ell}^D A_\ell^D \kappa^D(n_{2\ell}) + \frac{h^{L\prime}(N_1)}{h^L(N_1)} z_2^L J_{2\ell}^L A_\ell^L \kappa^L(n_{2\ell})\right] \phi_{2\ell} d\ell \\
&\geq w_2^* \int \left[\frac{h^{D\prime}(N_1)}{h^D(N_1)} z_2^D J_{2\ell}^D A_\ell^D \kappa^D(n_{1\ell}) + \frac{h^{L\prime}(N_1)}{h^L(N_1)} z_2^L J_{2\ell}^L A_\ell^L \kappa^L(n_{1\ell})\right] \phi_{2\ell} d\ell \\
&= w_1^* \int \left[\frac{h^{D\prime}(N_1)}{h^D(N_1)} \zeta z_1^D J_{1\ell}^D A_\ell^D \kappa^D(n_{1\ell}) + \frac{h^{L\prime}(N_1)}{h^L(N_1)} z_1^L J_{1\ell}^L A_\ell^L \kappa^L(n_{1\ell})\right] \phi_{1\ell} d\ell \\
&= w_1^* \zeta \left[h^{D\prime}(N_1)\bar{Q}_1^D C_D\left(h^D(N_1)\bar{Q}_1^D, h^L(N_1)\bar{Q}_1^L\right) + h^{L\prime}(N_1)\bar{Q}_1^L C_L\left(h^D(N_1)\bar{Q}_1^D, h^L(N_1)\bar{Q}_1^L\right)\right] \\
&= \zeta w_1^* \frac{dC\left(h^D(N_1)\bar{Q}_1^D, h^L(N_1)\bar{Q}_1^L\right)}{dN_1} \\
&= \zeta \sigma_1
\end{aligned}$$

where the first and last lines are the definition of σ_j, the third and third-to-last lines use the first order conditions for $\bar{Q}_j^D$ and $\bar{Q}_j^L$, the first inequality follows from the log convexity of h^D and h^L, the second inequality from $n_{2\ell} \geq n_{1\ell}$, and the next equality from $J_{2\ell}^L = J_{1\ell}^L$, $J_{2\ell}^L = J_{1\ell}^L$, $\phi_{2\ell} = \phi_{1\ell}$, and the definition of ζ. ■

A.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 $\frac{J_{j\ell}^D A_\ell^D}{J_{j\ell}^L A_\ell^L}$ and let $\zeta = \frac{z_2^D}{z_1^D} = \frac{z_2^L}{z_1^D} > 1$, 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.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

$$\lambda_2^D \mathcal{D}(r_2^D) > \lambda_1^D \mathcal{D}(r_1^D)$$
$$\lambda_2^L \mathcal{L}(r_2^L) < \lambda_1^L \mathcal{L}(r_1^L)$$

Consider a location in which $Q_{2\ell}^D \geq Q_{1\ell}^D$ is the same and $n_{1\ell} > 0$. Letting $x_{j\ell}^D \equiv Q_{j\ell}^D \lambda_j^D \mathcal{D}(r_j^D)$ and $x_{j\ell}^L \equiv Q_{j\ell}^L \lambda_j^L \mathcal{L}(r_j^L)$, the FOCs imply

$$A_\ell^D x_{2\ell}^D \kappa^{D\prime}(n_{2\ell}) + A_\ell^L x_{2\ell}^L \kappa^{L\prime}(n_{2\ell}) \leq \psi_\ell + \sigma_2 = \psi_\ell + \sigma_1 = A_\ell^D x_{1\ell}^D \kappa^{D\prime}(n_{1\ell}) + A_\ell^L x_{1\ell}^L \kappa^{L\prime}(n_{1\ell})$$

This can be rearranged as

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

and further as

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

Since $\frac{\lambda_1^D \mathcal{D}(r_1^D)}{\lambda_2^D \mathcal{D}(r_2^D)} < 1$, $\frac{x_{1\ell}^D}{x_{2\ell}^D}$ 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 $Q_{1\ell}^L \geq Q_{2\ell}^L$ and $n_{2\ell} > 0$. The FOCs imply

$$A_\ell^D x_{2\ell}^D \kappa^{D\prime}(n_{2\ell}) + A_\ell^L x_{2\ell}^L \kappa^{L\prime}(n_{2\ell}) = \psi_\ell + \sigma_2 = \psi_\ell + \sigma_1 \geq A_\ell^D x_{1\ell}^D \kappa^{D\prime}(n_{1\ell}) + A_\ell^L x_{1\ell}^L \kappa^{L\prime}(n_{1\ell})$$

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.5 Proof of Proposition 6

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

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

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

$$\frac{\lambda_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\lambda_j^D \mathcal{D}\left(r_j^D\right) B_j^D} = \frac{\mathcal{C}_L}{\mathcal{C}_D}$$

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

Recall that $\mathcal{C}(N, \bar{Q}^D, \bar{Q}^D) = C\left(h^D(N)\bar{Q}^D, h^L(N)\bar{Q}^L\right)$. Since C is homothetic, $\frac{\mathcal{C}_L}{\mathcal{C}_D}$ depends only on $\frac{\bar{Q}_j^L}{\bar{Q}_j^D}$, holding fixed N_j. 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:

$$\begin{aligned} \frac{\bar{Q}_j^D \mathcal{C}_{DD}}{\mathcal{C}_D} d\log \bar{Q}_j^D + \frac{\bar{Q}_j^L \mathcal{C}_{DL}}{\mathcal{C}_D} d\log \bar{Q}_j^L &= d\log B_j^D \\ \frac{\bar{Q}_j^D \mathcal{C}_{LD}}{\mathcal{C}_L} d\log \bar{Q}_j^D + \frac{\bar{Q}_j^L \mathcal{C}_{LL}}{\mathcal{C}_L} d\log \bar{Q}_j^L &= d\log B_j^L \end{aligned}$$

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:

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

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.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

$$\frac{\lambda_j^L \mathcal{L}\left(r_j^L\right) B_j^L}{\lambda_j^D \mathcal{D}\left(r_j^D\right) B_j^D} = \frac{\mathcal{C}_L}{\mathcal{C}_D}$$

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

Taking logs and differentiating each gives

$$-\left(\varepsilon_j^\lambda + \varepsilon_j^X\right) d\log\left(1+\omega_j\right) + d\log\frac{B_j^L}{B_j^D} = \chi_j d\log\frac{\bar{Q}_j^L}{\bar{Q}_j^D} \tag{28}$$

$$d\log\left(1+\omega_j\right) = d\log\frac{\bar{Q}^L}{\bar{Q}^D} - \varepsilon_j^X d\log\left(1+\omega_j\right) + d\log\frac{B_j^L}{B_j^D} \tag{29}$$

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 (28), this is

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

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

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

■

B Additional Model Details

B.1 Household Problem

Household i's demand for deposits and for loans depend 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, $\tilde{Q}_{j\ell}^D$ and $\tilde{Q}_{j\ell}^L$, as well as idiosyncratic components, $\varepsilon_{ij}^D, \varepsilon_{ij}^L$.

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

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

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

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

where the terms in the denominators are

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

For bank j, local deposits and local demand will be

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

Define the following objects:

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

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

$$
\begin{aligned}
D_{j\ell} &= T^D\left(\delta_{o_{j\ell}^D,\ell}\right)Q_{j\ell}^D A_\ell^D \mathcal{D}\left(r_{j,o_{j\ell}^D}^D\right)\\
L_{j\ell} &= T^L\left(\delta_{o_{j\ell}^L,\ell}\right)Q_{j\ell}^L A_\ell^L \mathcal{L}\left(r_{j,o_{j\ell}^L}^D\right)
\end{aligned}
$$

B.2 Details on Limiting Case

B.2.1 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

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

subject to $N_j = |O_j|$ and

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

We can divide the bank's problem into two stages, first selecting branch locations O_j and then making the remainder of its choices. We can characterize the second step as

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

where

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

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

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

subject to

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

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

B.2.2 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 span of control costs are given by

$$H^{D,\Delta}(|O_j|) = h^D\left(\Delta^2 |O_j|\right)$$
$$H^{L,\Delta}(|O_j|) = h^L\left(\Delta^2 |O_j|\right)$$

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 B.1 shows the firms profit in the limiting economy

Proposition B.1 *Let $\mathcal{N}$ be the set of positive functions $n : \mathcal{S} \to [0, \infty)$. In the limit, the bank's profit converges to*

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

where

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

where $\kappa^D(n) \equiv n g^D\left(\frac{1}{n}\right)$ and $\kappa^L(n) \equiv n g^L\left(\frac{1}{n}\right)$, 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).

B.3 A Convenient Functional Form

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

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

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

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

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

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

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

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

C Additional Empirical Results and Details

C.1 Data Cleaning

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 banks appear to be acquired by a new holding company that only owns a single bank. 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 ≠ 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.

C.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 can be written as

$$\frac{D_{j\ell}}{n_{j\ell}} = \bar{Q}_j^D J_{j\ell}^D \phi_{j\ell} A_\ell^D \mathcal{D}\left(r_j^D\right) \frac{\kappa^D\left(n_{j\ell}\right)}{n_{j\ell}}. \tag{30}$$

Converting the location index ℓ to counties, c, this result suggests the following regression specification:

$$\log \frac{D_{jct}}{n_{jct}} = \beta \times \text{Distance from Headquarters}_{jc} + \mathscr{P}(\text{Branches}_{jct}) + \delta_{jt} + \delta_{ct} + \epsilon_{jct} \tag{31}$$

where $\mathscr{P}(\text{Branches}_{jct})$ is a degree 5 polynomial in the number of branches placed by bank j in county c at time t. The estimate $\widehat{\beta}$ will tell us how $Q_{j\ell}$ varies with distance. As shown in Table C.3, we find $\beta < 0$ across all specifications, suggesting that appeal declines with distance.

C.3 Density of Initial Location and Bank Expansion

We consider the following regressions,

$$\log(\mathbb{E}[Y_{j,T_j} - Y_{j,0_j}]) = \beta \log(\text{Density}_{c_j^{HQ},0_j}) + \delta \text{Size}_{j,0_j} + \alpha \log(Y_{j,0_j}) + \gamma_{T_j} \times \gamma_{0_j} + \gamma_{s_j^{HQ}} + \varepsilon_j \ , \quad (32)$$

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

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

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 C.4. Columns (1) and (4) present the results for the Poisson regressions (32), columns (2) and (5) present the results for the Poisson regressions (33), and columns (3) and (6) present the results for the regression in log changes (34).

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.

C.4 Persistence of Local Deposit Abundance Measure

This section reports the persistence our deposit abundance measure, DepAbun_{ct}. For three different measures of local lending — mortgage loans, CRA small business loans, and the sum of the two — we estimate the R^2 of the regressions

$$\log \text{DepAbun}_{ct} = \alpha_k + \beta_k \log \text{DepAbun}_{ct-k} + \varepsilon_{ct}. \quad (35)$$

We consider two different time periods: 1990-2006 (when our mortgage data sample begins) and 1996-2006 (when our CRA small business loan sample begins). For 1990-1995, we plot the backfilled value of CRA small business loans that we use in the main text. We consider 5 years of lags in our plots. Figure C.3 reports the results graphically.

We find that DepInt_{ct} displays significant persistence over time, even at long time horizons. Further, note that even when only using mortgage loans, the persistence is stable across time periods, implying that the differences across time are not particularly important. This justifies our use of backfilling as a means of approximating deposit abundance for years in which we have missing data.

C.5 Additional Figures and Tables

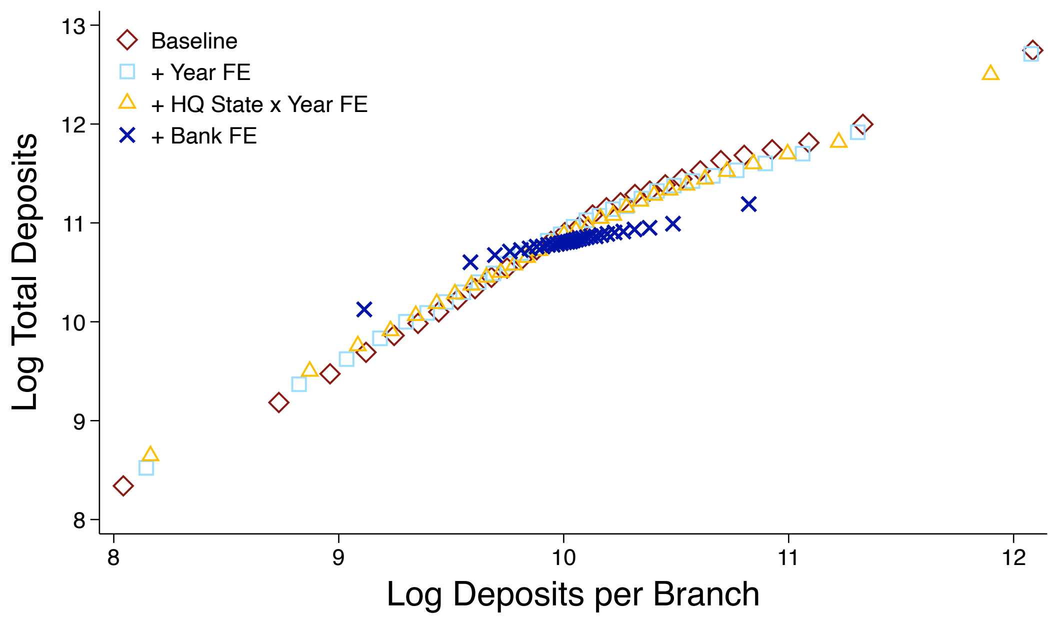
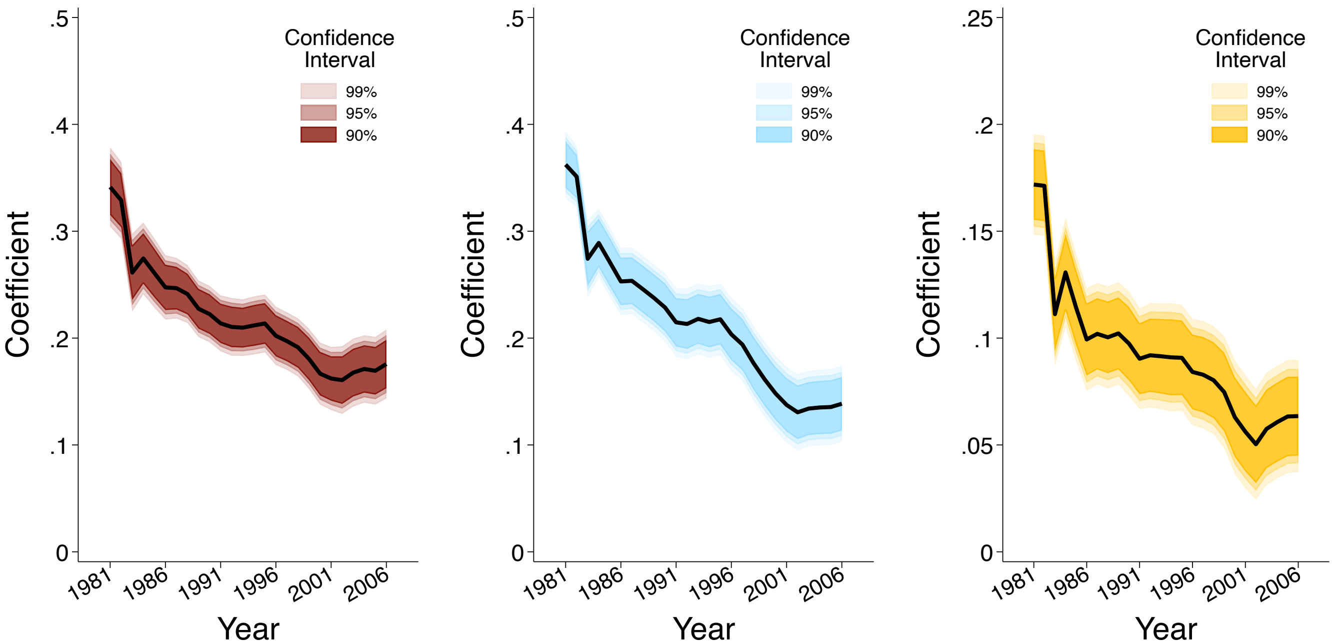
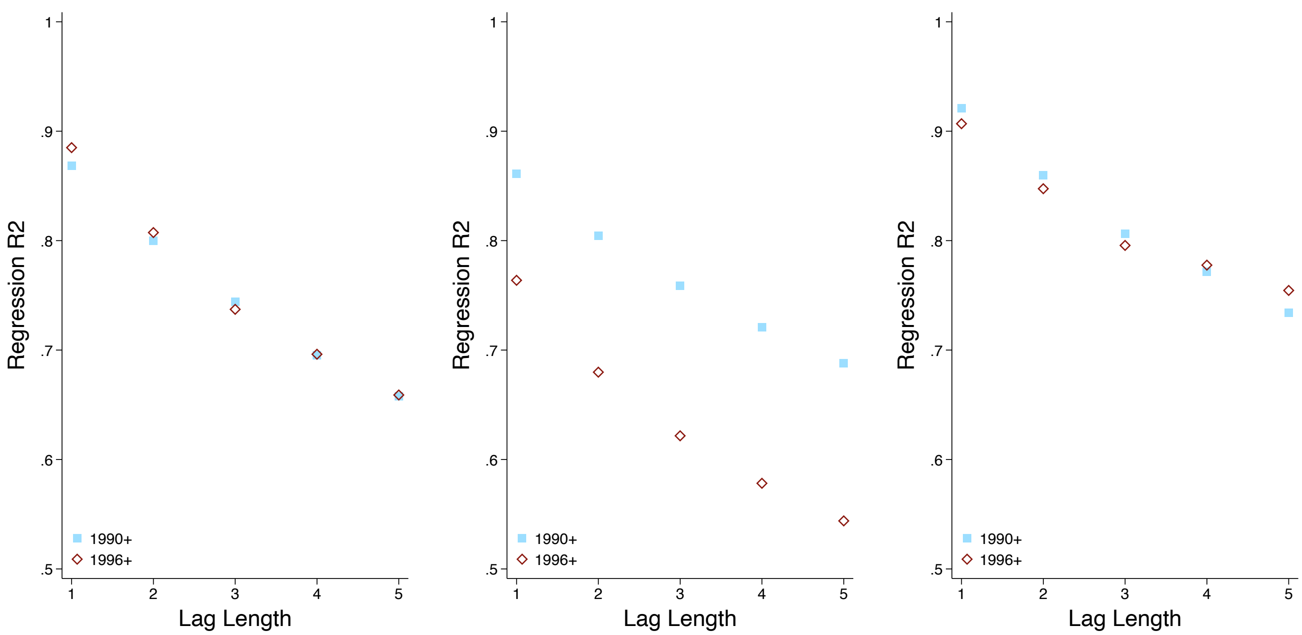


Figure C.1: This graph reports a binscatter plot of the relationship between log total deposits and log deposits per branch. Red diamonds report the raw relationship, blue squares add year fixed effects, yellow triangles add headquarter state by year fixed effects, and dark blue X's add bank fixed effects.



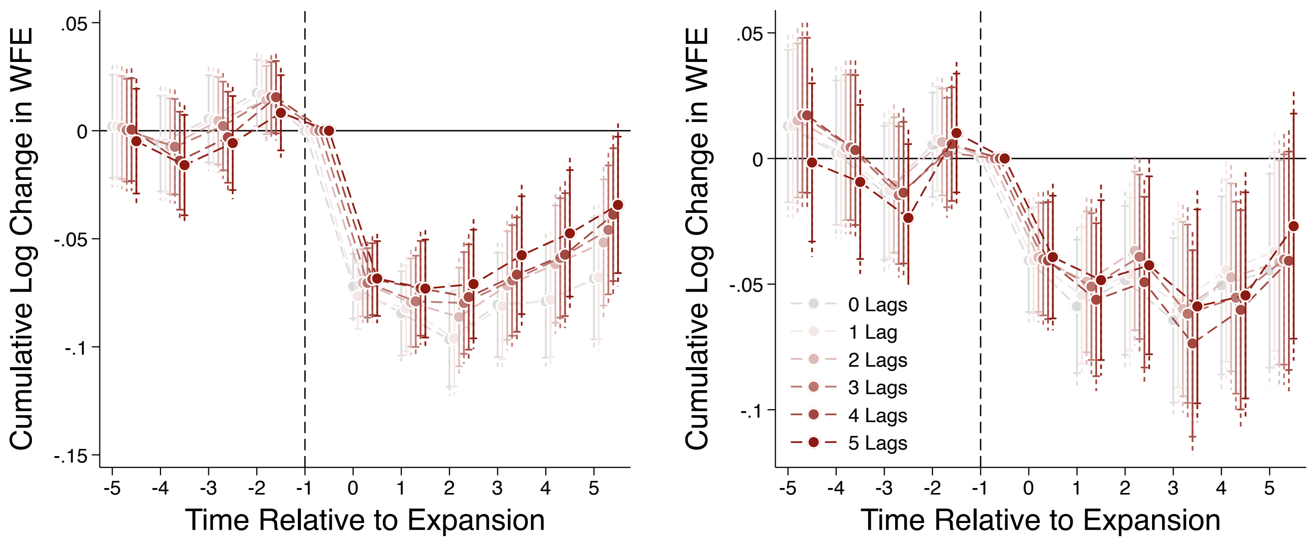
(a) State FE (b) State-HQ State FE (c) State-HQ CZ FE

Figure C.2: This figure reports the yearly regression coefficients for equation (16) using banks' log total deposits in the first year they appear in the sample as the main independent variable. Panel (a) uses state-by-year fixed effects, panel (b) uses state-by-headquarter state-by-year fixed effects, and panel (c) uses state-by-headquarter commuting zone-by-year fixed effects. Standard errors are clustered at the bank level.



(a) Mortgage Loans (b) CRA Loans (c) Total Loans

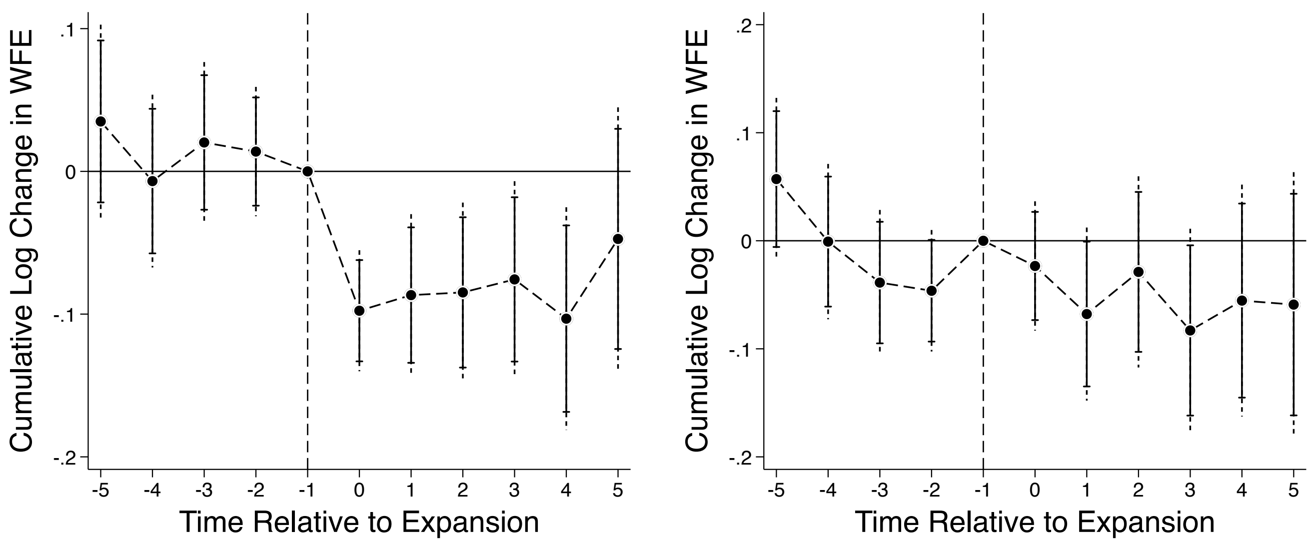
Figure C.3: This figure plots the R^2 from the regression (35). In the measure of deposit abundance, panel (a) only uses mortgage loans, panel (b) only uses CRA small business loans, and panel (c) uses both loans combined. Red diamonds report the results for the sample of counties between 1996-2006 and blue squares report results for the sample of counties between 1990-2006.



(a) Relative Effect of High WFE

(b) Relative Effect of Deposit Abundance

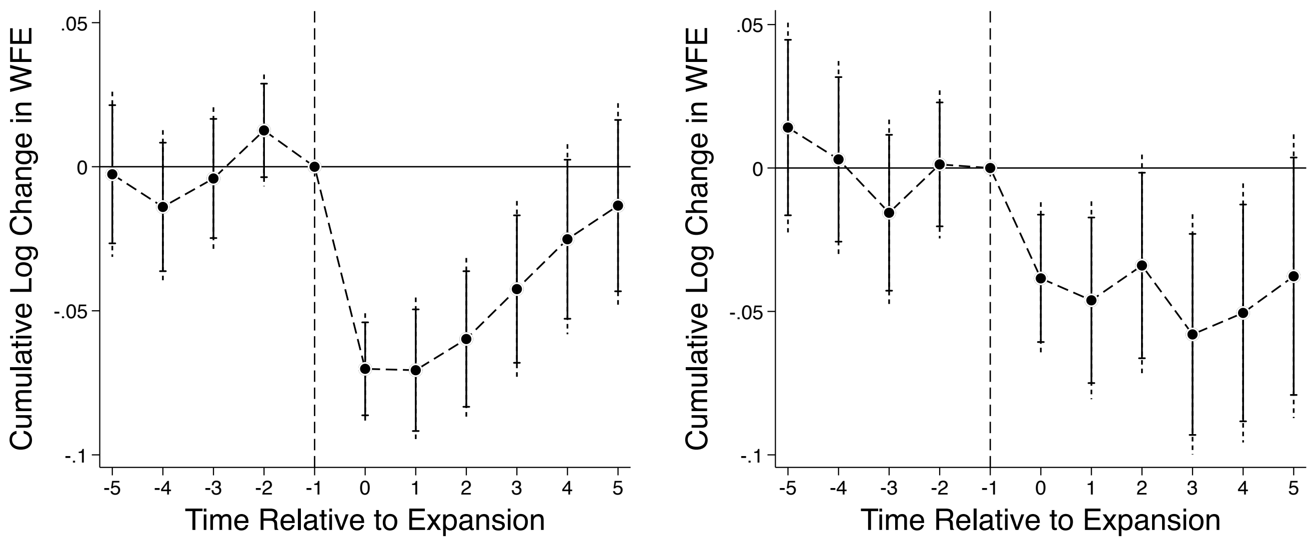
Figure C.4: This figure plots the regression estimates for equations (24) [Panel (a)] and (25) [Panel (b)]. We vary the number of lags of the expansion indicator in each equation from 0 to 5. Estimates are reported for time horizons $h = -5, \ldots, 5$, with $h = -1$ normalized to 0. Panel (a) reports the relative effect between high and low wholesale funding banks. Panel (b) reports the relative effect between high and low deposit abundant expansion. Standard errors are adjusted for heteroscedasticity. 90% confidence intervals are reported as solid lines, while the 95% confidence intervals are reported as dotted lines.



(a) Relative Effect of High WFE

(b) Relative Effect of Deposit Abundance

Figure C.5: This figure plots the regression estimates for equations (24) [Panel (a)] and (25) [Panel (b)]. This specification selects on banks that expand at most once throughout our sample. Estimates are reported for time horizons $h = -5, \ldots, 5$, with $h = -1$ normalized to 0. Panel (a) reports the relative effect between high and low wholesale funding banks. Panel (b) reports the relative effect between high and low deposit abundant expansion. Standard errors are adjusted for heteroscedasticity. 90% confidence intervals are reported as solid lines, while the 95% confidence intervals are reported as dotted lines.



(a) Relative Effect of High WFE

(b) Relative Effect of Deposit Abundance

Figure C.6: This figure plots the regression estimates for equations (24) [Panel (a)] and (25) [Panel (b)]. This specification selects on banks that ever expand at some point throughout our sample. Estimates are reported for time horizons $h = -5, \ldots, 5$, with $h = -1$ normalized to 0. Panel (a) reports the relative effect between high and low wholesale funding banks. Panel (b) reports the relative effect between high and low deposit abundant expansion. Standard errors are adjusted for heteroscedasticity. 90% confidence intervals are reported as solid lines, while the 95% confidence intervals are reported as dotted lines.

	Dependent Variable: $\log \text{Density}_{jst}$				
	(1)	(2)	(3)	(4)	(5)
Dep/Branch_{j0}	0.228***	0.300***	0.261***	0.259***	0.242***
	(0.017)	(0.050)	(0.059)	(0.079)	(0.073)
Out-of-State Only		✓	✓	✓	✓
Drop No HQ Overlap					✓
State × Year FE	✓	✓			
HQ State × State × Year FE			✓		
HQ CZ × State × Year FE				✓	✓
Obs.	220839	11821	8366	5299	4803
Adjusted R^2	0.41	0.48	0.56	0.67	0.65
Within R^2	0.02	0.04	0.04	0.05	0.04

Table C.1: This table reports regression estimates for the equation $\log \text{Density}_{jst} = \beta \log \text{Dep/Branch}_{j0} + \text{fixed effects} + \varepsilon_{jst}$. The dependent variable is the branch-weighted average log density of a BHC j in state s at time t. Dep/Branch_{j0} is the log deposits per branach of BHC j in their initial sample year. Column (1) includes the full sample of BHCs. Column (2) conditions on out-of-state banks. Column (3) further limits the variation to out-of-state BHCs headquartered in the same state. Column (4) limits the variation to out-of-state BHCs headquartered in the same commuting zone. Column (5) drops banks whose BHC headquarter commuting zone does not overlap with their largest member bank's headquarter commuting zone. Standard errors are reported in parentheses and clustered at the BHC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: $\log \text{DepAbun}_{ct}$					
Specification:	Mortgages + CRA Loans			Mortgages Loans Only		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \text{Density}_{ct}$	-0.356***	-0.374***	-0.359***	-0.456***	-0.475***	-0.481***
	(0.012)	(0.014)	(0.024)	(0.014)	(0.016)	(0.028)
$\log \text{Income}_{ct}$			-1.028***			-1.283***
			(0.102)			(0.117)
ShareAbove65_{ct}			8.392***			11.473***
			(0.430)			(0.513)
ShareWhite_{ct}			-0.903***			-1.066***
			(0.121)			(0.134)
$\text{ShareSelfEmployed}_{ct}$			-0.620***			-1.960***
			(0.163)			(0.185)
$\log \text{Branches}_{ct}$			0.101***			0.086**
			(0.036)			(0.043)
$\log \text{Banks}_{ct}$			0.091**			0.145***
			(0.041)			(0.048)
State-Year FE		✓	✓		✓	✓
Obs.	51073	51073	50204	51075	51075	50204
Within R^2	0.20	0.25	0.40	0.15	0.22	0.38

Table C.2: This table reports the regression results of equation (18). The dependent variable is the log of county c's deposit abundance in year t. Columns (1)-(3) use mortgages and CRA loans, while columns (4)-(6) only use mortgage loans. Controls are log population density, log of per capita income, the share of households above the age of 65, the share of white households, the share of self-employed workers, the log of the total number of branches, and the log of the total number of banks for each county. Standard errors are reported in parentheses and are clustered at the county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Dependent Variable:	log Dep/Branch$_{jct}$			log Deposits$_{jct}$		
	(1)	(2)	(3)	(4)	(5)	(6)
log Distance$_{jc}$	−0.118***	−0.121***	−0.111***	−0.229***	−0.234***	−0.226***
	(0.011)	(0.011)	(0.015)	(0.016)	(0.017)	(0.022)
Branches$_{jct}$	11.520***	11.068***	8.862***	60.839***	59.573***	51.900***
	(0.845)	(0.856)	(1.008)	(2.702)	(2.695)	(2.621)
Branches$^2_{jct}$	−33.663***	−32.212***	−24.832***	−182.775***	−177.899***	−146.998***
	(3.580)	(3.557)	(3.618)	(14.494)	(14.402)	(12.921)
Branches$^3_{jct}$	37.331***	35.640***	26.732***	204.763***	199.136***	160.204***
	(5.068)	(5.017)	(4.712)	(22.264)	(22.139)	(19.107)
Branches$^4_{jct}$	−16.314***	−15.552***	−11.482***	−90.335***	−87.819***	−69.620***
	(2.596)	(2.560)	(2.307)	(11.746)	(11.641)	(9.838)
Branches$^5_{jct}$	2.401***	2.286***	1.671***	13.422***	13.042***	10.247***
	(0.424)	(0.417)	(0.367)	(1.942)	(1.918)	(1.602)
Bank × Year FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Top 10% of Banks		✓			✓	
Top 1% of Banks			✓			✓
Observations	161867	126667	65766	161867	126667	65766
R^2	0.63	0.58	0.57	0.73	0.70	0.75
R^2	0.04	0.04	0.04	0.04	0.04	0.04

Table C.3: This table displays regression results of equation (31). The dependent variables are the log of bank j's deposits in county c divided by their branch density [Columns (1)-(3)] and the log of bank j's total deposits in county c [Columns (4)-(6)]. Distance$_{jc}$ is the total miles between the centroid of bank j's headquarter county and county c. 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 fifth degree polynomial in branch density $n_{j\ell}$. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	Branches			Counties		
	Poisson		Logs	Poisson		Logs
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \text{Density}_{c_j^{\text{HQ}},0_j}$	0.221**	0.242**	0.045***	0.120**	0.127*	0.007*
	(0.086)	(0.117)	(0.006)	(0.056)	(0.076)	(0.004)
$\log \text{Deposits}_{j,0_j}$	0.464***	0.416***	0.116***	0.546***	0.525***	0.084***
	(0.097)	(0.121)	(0.010)	(0.055)	(0.081)	(0.006)
$\log \text{Branches}_{j,0_j}$	0.406***	0.531***	−0.314***			
	(0.082)	(0.106)	(0.023)			
$\log \text{Counties}_{j,0_j}$				0.350***	0.506***	−0.292***
				(0.073)	(0.100)	(0.034)
First Year × Last Year FE	✓	✓		✓	✓	
HQ State FE	✓	✓		✓	✓	
First Year × Last Year × HQ State FE		✓	✓		✓	✓
Observations	16053	12642	14649	16091	9826	14649
Pseudo-R^2	0.74	0.80		0.59	0.63	
Within-R^2			0.06			0.04

Table C.4: This table displays the results of the Poisson regression equation (32) [Columns (1)-(2), (4)-(5)] and regression equation (34) [Columns (3) and (6)]. 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. $\log \text{Deposits}_{j,0_j}$ is the log of total deposits of bank j in the initial sample year. $\log \text{Branches}_{j,0_j}$ and $\log \text{Counties}_{j,0_j}$ are the initial number of bank j's branches and counties, respectively. Columns (1) and (4) consider separate time and headquarter state fixed effects, while the remaining columns interact the fixed effects. Standard errors are reported in parentheses and are clustered at the headquarter county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.295**		0.451***	0.300***
	(0.121)		(0.076)	(0.090)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.229**	0.102*	0.228***
		(0.098)	(0.062)	(0.080)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.446***
				(0.156)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.048
				(0.042)
$\log \text{Distance}_{jc}$	−0.774**	−1.204***	−1.319***	−1.330***
	(0.366)	(0.299)	(0.266)	(0.270)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Dep/Branch Decile × Density Decile FE		✓		
Obs.	6090	5547	11302	11302
Pseudo-R^2	0.67	0.66	0.69	0.70

Table C.5: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification includes banks with wholesale funding exposure greater than 1. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.700***		0.544***	0.342**
	(0.259)		(0.155)	(0.165)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.422***	0.256***	0.359***
		(0.156)	(0.092)	(0.117)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.303
				(0.280)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.110
				(0.075)
$\log \text{Distance}_{jc}$	−0.872**	−1.583***	−1.587***	−1.603***
	(0.374)	(0.345)	(0.345)	(0.347)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
. . . × WFE Decile × DepAbun Decile FE	✓			
. . . × Dep/Branch Decile × Density Decile FE		✓		
Obs.	3889	3552	7742	7742
Pseudo-R^2	0.63	0.62	0.68	0.68

Table C.6: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification only includes banks' branches that did not exist in a state prior to the bilateral opening event. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.472***		0.551***	0.331***
	(0.125)		(0.071)	(0.099)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.214**	0.150***	0.312***
		(0.098)	(0.056)	(0.080)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.537***
				(0.166)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.072*
				(0.041)
$\log \text{Distance}_{jc}$	−0.937***	−1.089***	−1.177***	−1.188***
	(0.282)	(0.296)	(0.217)	(0.222)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Dep/Branch Decile × Density Decile FE		✓		
Obs.	3671	3530	7377	7377
Pseudo-R^2	0.68	0.67	0.70	0.70

Table C.7: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification only includes observations between 1990 and 2006. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.461***		0.549***	0.322***
	(0.131)		(0.080)	(0.102)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.056	0.075**	0.150***
		(0.060)	(0.031)	(0.043)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.213**
				(0.084)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.091**
				(0.044)
$\log \text{Distance}_{jc}$	−0.713**	−1.246***	−1.342***	−1.359***
	(0.316)	(0.307)	(0.263)	(0.265)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Dep/Branch Decile × Density Decile FE		✓		
Obs.	5633	5172	10647	10647
Pseudo-R^2	0.69	0.65	0.70	0.70

Table C.8: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification only uses mortgage loans in the measure of deposit abundance. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Deposits}_{js} \times \log \text{Density}_{ch}$	0.016		0.142***	0.038
	(0.071)		(0.032)	(0.038)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.155*	0.122*	0.291***
		(0.083)	(0.063)	(0.074)
$\log \text{Deposits}_{js} \times \log \text{DepAbun}_{ch}$				−0.224***
				(0.059)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.136***
				(0.040)
$\log \text{Distance}_{jc}$	−0.763**	−1.222***	−1.261***	−1.308***
	(0.388)	(0.303)	(0.261)	(0.257)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
. . . × WFE Decile × DepAbun Decile FE	✓			
. . . × Size Decile × Density Decile FE		✓		
Obs.	5629	5981	10647	10647
Pseudo-R^2	0.65	0.67	0.69	0.70

Table C.9: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification uses the log of total deposits as the measure of bank productivity. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.414***		0.532***	0.425***
	(0.136)		(0.078)	(0.122)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.252**	0.144**	0.289***
		(0.105)	(0.061)	(0.078)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.088
				(0.191)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.064
				(0.040)
$\log \text{Deposits}_{js} \times \log \text{Density}_{ch}$				−0.043
				(0.040)
$\log \text{Deposits}_{js} \times \log \text{DepAbun}_{ch}$				−0.202***
				(0.066)
$\log \text{Distance}_{jc}$	−0.781**	−1.195***	−1.318***	−1.336***
	(0.359)	(0.299)	(0.265)	(0.264)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Size × Dep/Branch × Density Decile FE		✓		
Obs.	5629	5008	10647	10647
Pseudo-R^2	0.65	0.65	0.70	0.70

Table C.10: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification includes additional controls for bank size (measured as total deposits) in addition to using deposits per branch as a measure of bank productivity. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.255**		0.341***	0.191**
	(0.109)		(0.066)	(0.083)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.190**	0.118*	0.212***
		(0.081)	(0.062)	(0.077)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.232*
				(0.129)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.100**
				(0.042)
$\log \text{Distance}_{jc}$	−0.770**	−1.211***	−1.317***	−1.335***
	(0.372)	(0.300)	(0.261)	(0.261)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Dep/Branch Decile × Density Decile FE		✓		
Obs.	5629	5490	10647	10647
Pseudo-R^2	0.65	0.68	0.69	0.69

Table C.11: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification uses banks' deposits per branch in the initial year they appear in the sample rather than the year prior to a bilateral opening event. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{jt} \times \log \text{Density}_{ct}$	0.473***		0.599***	0.377***
	(0.106)		(0.089)	(0.104)
$\log \text{WFE}_{jt} \times \log \text{DepAbun}_{ct}$		0.084	0.122***	0.262***
		(0.073)	(0.046)	(0.068)
$\log \text{Dep/Branch}_{jt} \times \log \text{DepAbun}_{ct}$				−0.472***
				(0.165)
$\log \text{WFE}_{jt} \times \log \text{Density}_{ct}$				0.081**
				(0.038)
$\log \text{Distance}_{jc}$	−0.807***	−1.748***	−1.294***	−1.328***
	(0.278)	(0.342)	(0.259)	(0.263)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
... × WFE Decile × DepAbun Decile FE	✓			
... × Dep/Branch Decile × Density Decile FE		✓		
Obs.	5773	5365	11033	11033
Pseudo-R^2	0.67	0.67	0.69	0.69

Table C.12: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification uses time t measures of bank and county variables rather than measuring them the year before a bilateral opening event. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

	Dependent Variable: Branches_{jct}			
	(1)	(2)	(3)	(4)
$\log \text{Dep/Branch}_{js} \times \log \text{Density}_{ch}$	0.416***		0.493***	0.329***
	(0.081)		(0.057)	(0.063)
$\log \text{WFE}_{js} \times \log \text{DepAbun}_{ch}$		0.028	−0.008	0.071
		(0.061)	(0.044)	(0.045)
$\log \text{Dep/Branch}_{js} \times \log \text{DepAbun}_{ch}$				−0.176*
				(0.092)
$\log \text{WFE}_{js} \times \log \text{Density}_{ch}$				0.143***
				(0.025)
$\log \text{Distance}_{jc}$	−0.807***	−1.371***	−1.103***	−1.111***
	(0.238)	(0.257)	(0.194)	(0.194)
Out-of-State Only	✓	✓	✓	✓
Bank × State × Year FE	✓	✓	✓	✓
County × HQ State × Year FE	✓	✓	✓	✓
HQ CZ × State × Year FE	✓	✓	✓	✓
. . . × WFE Decile × DepAbun Decile FE	✓			
. . . × Dep/Branch Decile × Density Decile FE		✓		
Obs.	9550	9606	16689	16689
Pseudo-R^2	0.69	0.68	0.71	0.71

Table C.13: This table reports the results of Poisson regression equations (20) [Column (1)], (21) [Column (2)], and (22) [Columns (3) and (4)]. This specification only includes observations 6-10 years after a bilateral opening event. Independent bank and county variables are measured in the year prior to a bank-state pair opening event. We consider observations 0-5 years after the opening event occurs. Standard errors are reported in parentheses and are clustered at the bank-county level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.