Banks' Geographic Expansion: New Location, Same Old Neighbours

Ka-leung Lam [*]

December 4, 2025

Link to latest version

Abstract

This paper examines how the spatial distribution of firms shapes banks' geographic expansion following deregulation. I first show that geographic overlap of operating areas between banks and firms is associated with persistent lending relationships. Then, I follow the development of the U.S. interstate banking deregulation, and find that banks are more likely to enter locations with higher shares of firms from their original neighborhood. The effects are stronger for banks focused on commercial & industrial loans, suggesting that pre-existing lending relationships facilitate entry. Moreover, these locations receive more credits from non-local banks and exhibit stronger employment growth.

[*]Monash University. Contact: Jialiang.Lin@monash.edu. I am grateful for continuous support and guidance from my thesis advisor Atif Mian. I appreciate the comments and suggestions from Ernest Liu, Kaveh Majlesi, Wei Xiong, Motohiro Yogo, as well as seminar participants at Princeton, NEOMA, UC3M, and Hanken School of Economics. All errors are my own.

1 Introduction

Financial development in the banking sector is often tied to the ability of banks to expand into new markets. A large literature, beginning with Jayaratne and Strahan (1996), shows that deregulating geographic restrictions on the banking sector lead to credit expansion and economic growth. The underlying rationale is that the physical presence of banks through branch establishments is crucial for credit provision, and that removing legal geographic restrictions enables non-local banks to reach local borrowers, increasing credit availability and enhancing productive capacity. While much is known about the aggregate consequences of deregulation, less is understood about the distributional impacts as banks choose where to expand their geographic footprints within the deregulated region.

In this paper, I show that the spatial distribution of firms shapes banks' geographic expansion and thus the outcomes of banking deregulation. Specifically, I follow banks' geographic footprints during the U.S. interstate banking deregulation episode, and find that they are more likely to enter locations with higher shares of firms from their original neighbourhood. Moreover, these locations receive more credits from non-local banks and experience stronger employment growth following the deregulation. Hence, a state-wide financial liberalisation has differential impacts across geographic locations within the deregulated state. I provide evidence that these patterns are driven by pre-existing lending relationships between banks and their neighbouring firms.

I start by showing that geographic overlap of operating areas between banks and firms is associated with material lending relationships. This evidence not only supports the idea that the effects of old neighbours on entry is driven by pre-existing lending relationships, but also that the effects on credit provision in the deregulated regions is driven by entry. Using a novel dataset that merge corporate loan contracts from DealScan, firm establishment locations from Dun & Bradstreet, and bank branch information from the Summary of Deposits, I show that: (1) Despite limited observations of the loan dataset in the early years, a significant fraction of large multistate firms do show up, suggesting that these firms do rely on bank credit; (2) Firms are more likely to borrow from neighbouring banks with overlapping areas of operation (in our case, counties); and (3) Lending relationships persist over time—firms tend to borrow from banks who have previously lent to them. These findings confirm that an enduring lending relationship exists between banks and firms operating in the same neighbourhood.

Then, I examine how this historical geographic proximity and the spatial distribution of firms affect banks' entry in the newly deregulated regions. If enabling local borrowers to access credits from non-local banks constitutes an important objective of banking deregulation, then whether these banks enter a location with more or less firms that may not have had access to non-local banks will make a difference in the outcomes. In fact, the experience from the U.S. interstate banking deregulation shows that it is the locations with greater presence of the bank's old neighboring firms that are more likely to receive entry. To establish the causal relationship, I first compile a schedule of the interstate banking deregulation at the state pair level. Next, for each deregulation event where a home state allows entry of banks from a foreign state, I designate banks headquartered in the foreign states as potential entrants and counties in the home state as potential destinations. Then I identify the old neighbouring firms of each entrant bank's as those operating in the counties where the bank also owns a branch one year prior to the deregulation. I measure the presence of these firm in the potential destinations by their employment shares. Finally, I estimate a linear probability model on bank entry outcomes following the deregulation, and find that a higher share of old neighbours is associated with a higher likelihood of entry. By including an extensive set of bank and county fixed effects, the model controls for all bank and county characteristics that may drive the expansion. I also rule out the results being driven purely by geographic proximity to the destination by controlling for the distance between the bank's headquarters and the destination. Moreover, reverse causality is unlikely since I use the pre-deregulation firm locations to predict post-deregulation entry outcomes, and the timing of deregulation is plausibly exogenous to the banking and corporate sectors. The results are stronger for banks with a greater focus on commercial and industrial loans, consistent with pre-existing lending relationships driving the results.

Next, I document that the presence of old neighbouring firms further shapes the geographic distribution of credits of non-local banks in the deregulated regions. I continue to the exploit the merged DealScan-D&B dataset. To convert a loan contract into bank-county level observations, I distribute the loan across lenders and across borrower's areas of operations. While this does not necessarily capture where the funds are actually invested within a firm, it does capture where the establishments of the firm being financed are located, which is of primary interest for this part of the analysis. I show that firms in locations with a higher share of old neighbours receive more loans from non-local banks after deregulation. This pattern holds not only for loans to firms that have prior geographic overlap with the non-local banks but also for loans to firms that do not, suggesting that there are spillover effects on credit provision beyond the historically connected borrowers, but only to those located close to these borrowers.

Finally, I investigate the local aggregate real effects of bank expansion induced by pre-existing business relationships. Using county-level employment data from the County Business Patterns and a stacked difference-in-differences design, I find that counties with a greater presence of old neighbouring firms experience stronger employment growth following the deregulation.

This paper contributes to two main strands of the literature. First, it adds to research on the consequences of banking deregulation by documenting how historical economic connections influence the geographic pattern of bank entry, credit provision, and employment growth. While prior work pioneered by Jayaratne and Strahan (1996) has emphasized the aggregate gains from deregulation, this study shows that its benefits are unevenly distributed across locations and firms. Related studies such as Mian (2006) and Bofondi and Gobbi (2006) have highlighted the role of credit market frictions in shaping lending outcomes of entrant banks after deregulation. This paper explores outcomes along the new geographic dimension and highlights a new mechanism where banks leverage pre-existing lending relationships to facilitate expansion.

Second, it contributes to the literature on bank-firm relationship by showing that the geographic distribution of firms affect banks' expansion strategies. Related studies such as Chodorow-Reich (2014), Huber (2018) and Greenstone et al. (2020) have shown the effects of lending relationships on real outcomes during credit crunches. This paper shows the role of pre-existing lending relationships in shaping financial development and economic growth. The merged loan-firm-bank dataset constructed for the current study, in a similar fashion to Chodorow-Reich (2014), yet without access to confidential administrative records, also provides novel evidence on the spatial allocation of credits, in particular syndicated loans to large firms, which complements related research on small-business lending and home mortgage loans (e.g., Petersen and Rajan (2002) and Nguyen (2019)).

The rest of the paper is structured as follows. Section 2 describes data sources. Section 3 introduces relevant historical background about the U.S. interstate banking deregulation.

Section 4 provides evidence on lending relationship between firms and neighbouring banks. Section 5 discusses the empirical strategy and report the main results on entry outcomes. Section 6 examines lending outcomes in the deregulated regions. Section 7 investigates the heterogeneous real effects of banking deregulation within the deregulated states. Section 8 concludes.

2 Data

The analysis utilises data from multiple sources at the bank, firm, and loan levels.

The timing of interstate banking deregulation is documented by Amel (1993), based on which I compiled a chronology of newly deregulated state pairs (see Internet Appendix A). Note that oftentimes, these deregulation legislations included reciprocity requirements, meaning that a bank holding company (BHC) from state A could only enter state B if state A also allowed entry of BHCs from state B. Therefore, the effective date of deregulation of a home state allowing entry of banks from a foreign state depends on the legislations of both states.

The data regarding the locations of bank branches are sourced from the Summary of Deposits (SoD). The data for the later period (1987–) were obtained from the FDIC website.[1] For the earlier period (1981–1986), this information was acquired from the work of Christa H.S. Bouwman.[2] SoD includes details about the county locations of bank branches, the amount of deposits as of June 30 each year, and the identification of banks' ultimate parent holding companies. In the case of SoD from 1987 onwards, it also provides information about the headquarter counties of the parent BHCs, which I use to determine their home states. For the earlier period (1981–1986), I gathered information about BHCs' headquarter locations from FFIEC National Information Center online data repository.[3] Finally, bank balance sheet data comes from Call Reports.

Firm-level data are from Dun & Bradstreet (D&B). This database provides comprehensive information on the location, employment, and industry classification (SIC) of all busi-

[1] Data from 1987–1993 is available at `https://www.fdic.gov/foia/sod/`, and data from 1994 onwards can be found at `https://www.fdic.gov/bank/statistical/index.html`.

[2] Data for 1981–1993 is available in part D of the data page on `https://sites.google.com/a/tamu.edu/bouwman/home`.

[3] Data can be accessed at `https://www.ffiec.gov/NPW`

ness establishments across the United States. It also offers insights into the firm's internal ownership structure.

For the analysis of lending outcomes, I use data on syndicated loans from DealScan with deal active date spanning 1987—2005. I manually linked the loan data to D&B and SoD to obtain the borrower and lender information. Borrowers are matched with D&B firms based on company name, location, and industry information provided by both sources. They are then assigned identifiers (DUNSNO) from D&B. Lenders are matched with the ultimate parent BHCs in the SoD based on names and locations, and they are assigned identifiers (RSSDID) from SoD.

Finally, for the analysis of employment effects, I sourced data from County Business Patterns (CBP) spanning 1978—2008. This dataset provides information on employment count at the county level annually.

3 Historical Background

The empirical analysis of this paper leverages the natural experiment from interstate banking deregulation in the United States. During this period, the removal of legal entry barriers allowed bank holding companies (BHC) to operate across state borders. In this section, I provide an overview of the relevant institutional background regarding the interstate banking deregulation. I will focus particular features of the deregulation that facilitate my empirical design.

According to Amel (1993), the state of Maine was the first to eliminate its interstate banking restrictions and open its banking sector to all other states in 1978. However, Maine's approach included a reciprocity requirement, stating that out-of-state bank holding companies could only enter if the foreign state in which the BHC was headquartered also permitted entry of banks from Maine. No no other state took actions until 1982 when New York also passed its deregulation legislation. Afterwards, many states adopted similar measures and deregulated their banking industries. Ultimately, in 1994, a federal law called Riegle-Neal Interstate Banking and Branching Efficiency Act went into effect, essentially removing the remaining restrictions on banking activities across state borders.

The deregulation process is rather chaotic for two primary reasons. First, deregulation legislation often contained reciprocity provisions, similar to Maine's, making the ability of a bank to enter a deregulated state dependent on the banking regulations of its home state as well. Second, not all states opened their banking sectors to the entire country in a single legislation move; instead, they often began by opening to a set of designated states and gradually expanded the list over time. These features resulted in a complex and staggered pattern of deregulation across state pairs over time, which makes these events likely exogenous shocks to the banking and the corporate sectors.

Figure 1 visualises the evolution of the interstate banking deregulation. Panel A displays the number of newly deregulated state pairs each year, while Panel B shows the cumulative fraction of deregulated state pairs. The year of deregulation (for this figure and the rest of the paper) is the one in which a home state effectively permitted entry of BHCs from a foreign state, accounting for the reciprocity requirement in the relevant legislations. Each state pair is classified according to their deregulation status: "Unilateral" indicates that only one of the states allowed entry of BHCs from the other, while "Bilateral" indicates that BHCs headquartered in both states were allowed to enter each other's market. In Panel A, the deregulation status is classified based on the new legislation, while in Panel B, it is classified based on the current status of the state pair. For example, Texas deregulated in 1987 to allow entry of BHCs from Alabama, and Alabama also deregulated in 1988. Therefore, in Panel A, the state pair AL-TX is counted as one of the unilaterally deregulated pairs in 1987 and again as one of the unilaterally deregulated pairs in 1988. In Panel B, however, AL-TX is counted as one of the unilaterally deregulated pairs in 1987 and as one of the bilaterally deregulated pairs in 1988. The sample includes 47 contiguous states, with Hawaii excluded due to its remote geographic location, Alaska excluded due to its lack of regular county subdivisions, and Delaware and South Dakota excluded due to their special arrangements for credit card businesses. The final sample comprises 1,081 state pairs in total ($= 47 \times 46/2$). Panel A shows that during the most active deregulation years (1986–1991), around 150 state pairs that were involved in deregulation events, with the majority being unilateral deregulations.

Figure 2 illustrates the impact of interstate banking deregulation on the landscape of out-of-state bank holding companies. It compares the situation in 1981, one year before the interstate banking deregulation began, to 2006, over a decade after the passage of IBBE. Prior to deregulation, almost three-quarters of states had virtually zero presence of out-of-state BHCs. However, in 2006, out-of-state BHCs had become prevalent. Nearly all states had at least 10% of branches controlled by out-of-state BHCs, with some states exceeding 50%.

On the other hand, however, many firms were already operating across state borders before banks did. Panel A of Figure 3 displays the employment share of large multistate firms (those with more than 500 employees) in each state in 1980. Most states had at least 10% of the labour force employed by these multistate firms, with some states exceeding 40%. This makes it possible to examine the role of multistate firms in shaping banks' geographic expansion.

4 Lending Relationship

In this section, I provide evidence that the spatial overlap between banks and firms represent meaningful economic relationships. Using a novel dataset merging corporate loan data from DealScan with data on firm locations from Dun & Bradstreet and data on bank locations from Summary of Deposits, I show that (1) large multistate firms rely on bank credit, (2) these firms are more likely to borrow from geographically proximate banks, and (3) lending relationships persist over time.

Despite the fact that DealScan covers mostly syndicated loans, a specific type of corporate loans, and has limited observations in the earliest years, I find that a significant fraction of multistate firms, especially larger firms, appear in the database. This suggests that these firms do rely on banking credits. More importantly, conditional on borrowing, firms are more likely to borrow from neighbouring banks, and more likely to borrow from banks that had previously lent to them.

I start with a sample of DealScan loans by U.S. firms with deal active dates from 1987 to 1994, the period prior to the end of the deregulations.[4] Panel A of Figure 4 illustrates the total number of loans designated to U.S. borrowers (excluding financial and government entities) by DealScan in each year, as represented by the white bars. I manually matched these borrowers to D&B based on name, industry and location provided by both data sources. I associated these loans to the firm's ultimate parent, and retained only firms that operate across multiple states. I also matched the lenders to banks in the Summary of Deposits, and retained loans in which at least one U.S. bank was involved. This matching process reduced

[4]DealScan has very few observations before 1987.

the sample size by approximately two-thirds. The remaining loans, as represented by the grey bars in Panel A, are thus those borrowed by multistate firms and financed by at least one U.S. bank. Panel B of Figure 4 displays the number of unique multistate firms, with roughly 300 to over 1000 firms borrowing in any given year. Panel C shows the number of active lenders (BHCs) that appeared in at least 10 loans in a given year. There are approximately 50 active banks in each year.

First, I verify that multistate firms do rely on banking credits by showing that a significant portion of large multistate firms do appear in the previously constructed sample of DealScan loans. Panel A of Figure 5 shows the total number of large multistate firms that will be used to measure the presence of old neighbours in the upcoming main empirical analysis. These firms are non-financial, non-governmental entities with more than 500 employees and operate across multiple states. There are over 6,000 such firms, with one-third of them having more than 2,000 employees. Panel B of Figure 5 reproduces Panel B of Figure 4, representing the number of unique borrowing firms in the merged DealScan-D&B sample. Among these firms, more than half of them have over 2,000 employees, suggesting that borrowers covered by the loan data tend to be larger firms.

Panel C of Figure 5 shows the fraction of large multistate firms who borrowed a new loan in each year. The figure suggests that around 10% of large multistate firms carried out a new loan in a given year. This number is calculated by dividing the grey bars in Panel B with grey bars in Panel A. And these borrowing firms account for 20% to 50% of total employment by all large multistate firms. Panel D of Figure 5 shows that approximately 35% of these large multistate firms had borrowed at least once during the sample period, and they account for more than 70% of total employment. The coverage of firms becomes more significant for larger firms, as shown in Panels E and F of Figure 5. Among firms with more than 2,000 employees, approximately 10% to 30% of them borrowed in a given year, accounting for approximately 20% to over 50% of the employment of these firms. Furthermore, around 60% of these firms had ever borrowed at some point during the sample period, accounting for around 80% of the total employment by these firms.

Next, I show that geographic proximity shapes lending relationship, i.e., firms are more likely to borrow from neighbouring banks, I estimate the following linear probability model:

$$Loan_{fbt} = \beta[Neighbour]_{fbt} + \phi_{ft} + \phi_{bt} + \varepsilon_{fbt}, \tag{1}$$

where the dependent variable $Loan_{fbt}$ is an indicator for whether firm f borrows from bank b in year t, and the primary explanatory variable is an indicator $[Neighbour]_{fbt}$ which assumes a value of one if the bank operates in the same county where the firm also operates an establishment. Mathematically, this can be written as:

$$Neighbour_{fbt} = \mathbb{I}\{C_{ft} \cap C_{bt} \neq \emptyset\}. \tag{2}$$

where C_b represents the set of counties where bank b has a branch, and C_f the set of counties where firm f has an establishment. Table 1 reports the results from the above regression. The coefficients on $[Neighbour]_{fbt}$ are both positive and statistically significant, which suggests that firms are more likely to borrow from neighbouring banks rather than those located farther away. Specifically, the estimated value in column (2) is 4.02, suggesting that being neighbours increases the likelihood of lending by 4.02 percentage points. For comparison, the unconditional mean any bank being a lender is 7.79 percent.

Lastly, I examine the persistence of lending relationships by estimating the following linear probability model:

$$Loan_{bft} = \beta[Previous]_{bft} + \phi_{bt} + \phi_{ft} + \varepsilon_{bft} \tag{3}$$

where the dependent variable $Loan_{bft}$ is again an indicator for whether bank b lends to firm f in year t, and the key explanatory variable $[Previous]_{bft}$ is an indicator for whether bank b had lent to firm f the last time firm f borrowed. The sample consists of loans where the borrower has borrowed before. Table 2 reports the results from the above regression. The coefficients on $[Previous]_{bft}$ are both positive and statistically significant, which suggests that lending relationships are persistent over time. Specifically, the estimated value in column (2) is 48.3, suggesting that having lent to a firm in the previous year increases the likelihood of lending by 48.3 percentage points. For comparison, the unconditional mean any bank being a lender is 8.34 percent.

In summary, these findings confirm that lending relationships exist between banks and the neighbouring firms, and these relationships are persistent over time.

5 Old Neighbours and Bank Entry

In this section, I establish the link between the presence of a bank's old neighbouring firms in a new location and the bank's likelihood of entry following deregulation.

5.1 Specification

I estimate the following linear probability model for bank entry outcomes:

$$Entry_{bc,t(d)+h} = \beta\left[Old\ Neighbours\right]_{bc,t(d)-1} + \phi_{b,t(d)} + \phi_{c,t(d)} + \gamma X_{bc,t(d)-1} + \varepsilon_{bc,t(d)}, \qquad (4)$$

where, the dependent variable $Entry_{bc,t(d)+h}$ is an indicator of whether bank b enters county c, h years after the deregulation. It takes the value of one if, in year $t(d)+h$, a branch in county c is under control by bank b. The index d represents the event in which the state of county c deregulates its banking sector to the state where bank b is headquartered, and $t(d)$ indicates the year in which deregulation takes effect. The key explanatory variable $\left[Old\ Neighbours\right]_{bc,t(d)-1}$ measures the employment share in the destination county c by firms operating in bank b's original neighbourhood (to be defined shortly). It is computed in the year prior to deregulation. This variable reflects the strength of the existing connections between the potential entrant bank and the firms in the new location. A higher share of familiar old neighbours represents a stronger connections through the existing lending relationships, and is shown to increase the likelihood of entry. Variables $\phi_{b,t(d)}$ and $\phi_{c,t(d)}$ represent bank-year and county-year fixed effects, which absorb bank- or county- specific characteristics that may influence entry outcomes and correlate with the presence of the bank's old neighbours. For example, larger banks may have greater capacity to expand and may also be connected to a larger number of firms. Including the bank fixed effects will control for such size effects. Finally, variables X include controls that vary only across bank-county pairs. In particular, I include the geodesic distance between bank's headquarters and the destination county as a control. The distance captures the administrative costs of operating a new branch, and it is typically less costly to manage a branch nearby. However, it is likely that the same firms are also operating in those areas. Including distance as a control makes sure that the variable *Old Neighbours* is not simply capturing the effects of distance.

5.2 Sample and variables

To conduct the test described above, I construct a dataset with bank-county pairs as the unit of observation. For each deregulation event in which a state opened its banking sector to banks from other states, I designate the state initiating the deregulation as the "home state", and those whose banks were permitted entry as the "foreign states." This makes all counties in the home state potential destinations for entry. As for the potential entrants, I identify BHCs headquartered in the foreign states one year before the deregulation that have not entered the home state. To ensure the sample of banks to be most relevant for studying geographic expansion, I only include banks that are reasonably sizable (i.e., those having over one billion deposits ever), and that have ever expanded across state borders during the sample period (1982–2005). Each potential entrant bank is then associated with each potential destination county it is allowed to enter. Finally, I stack these bank-county pairs from all deregulation events to create a large cross-sectional dataset.

Figure 6 illustrates the sample size. Panel A shows the total number of banks as potential entrants for each year of deregulation, while Panel B shows the total number of counties within the deregulated states. Notably, during the most active years of deregulation, there were more than 200 banks permitted to enter new markets, with approximately 1,500 counties becoming potential destinations.

Next, I measure the presence of old neighbouring firms across newly deregulated locations for each potential entrant. I first define a bank b and a firm f being neighbours in year t if they operate in the same county, as in Equation 2. I then calculate the employment share of bank b's old neighbours in a destination county c as:

$$[Old\ Neighbours]_{bct} = \frac{\sum_f Employment_{fct} \times Neighbour_{fbt}}{\sum_f Employment_{fct}}, \tag{5}$$

where the numerator represents the employment by the bank's neighbouring firms and the denominator is the total employment of the county.

Panel A of Figure 7 shows the number of firms used to construct the variable *Old Neigh-*

bours. These firms are non-financial and non-government entities with more than 500 employees, operating across multiple states. There are approximately 6,000 of them, with about one-third having more than 2,000 employees. Note that D&B data were not produced for years 1981 and 1984. Therefore, when data from these two years are needed, I use the data from the previous year (i.e., 1980 and 1983 respectively). Panel B of Figure 7 presents the distribution of the variable *Old Neighbours* across bank-county pairs. For illustrative purpose, approximately 15% of the observations with a value of zero are omitted from the figure. The last bin of the histogram includes all values greater than 40%. The figure reveals substantial variation in the variable of interest. The sample mean (including zeros) is 8.8%, while the median is 4.9%. The standard deviation is 10.6%.

5.3 Timing

Before presenting the results on entry outcomes, I assess the speed of entry by conducting the following event study using a state-pair panel dataset:

$$FrgnBankShare_{ijh} = \phi_{ij} + \sum_{r \neq -1} \beta_r \mathbb{1}_{r=h}, \tag{6}$$

where the dependent variable $FrgnBankShare_{ijh}$ measures the extent of penetration in the home state i by banks from foreign state j, h years since the deregulation. I create two measures of penetration rate: the fraction of counties entered by out-of-state BHCs and the share of branches owned by those banks. ϕ_{ij} represents state-pair fixed effects. Therefore, the coefficients of interest, β_r's, measures the average change in penetration rate over time, relative to the year before deregulation.

Figure 8 plots the estimates of β_r's from four years prior to deregulation to fifteen years after. The coefficient for the year immediately before deregulation is normalised to zero. The figure suggests that entries occur rapidly within the first three years following deregulation, with penetration rates reaching their peak in approximately the tenth year before stabilising. Both penetration measures exhibit similar patterns.

In the following section, I report results on entry outcomes in both the short term (two years since deregulation) and the long term (ten years since deregulation). Additional results on other time horizons can be found in the Internet Appendix C.

5.4 Entry outcomes

Table 3 reports results from the model in Equation 4. The coefficients are scaled up by 100. In column (1), where I estimate the likelihood of entry two years after deregulation, the estimated coefficient on *Old Neighbours* is 1.15, indicating that a one-standard-deviation (i.e., 10.5 percentage points) increase in the employment share by the bank's old neighbours increases the probability of entry by 11.5 basis points. This magnitude is nearly two thirds of the unconditional mean (19 bp) of the dependent variable.

Column (2) introduces the control for geodesic distance between bank headquarters and destination counties. The negative coefficient on distance suggests that a longer distance leads to a reduced likelihood of entry. While the coefficient on *Old Neighbours* is slightly smaller in magnitude, reflecting its partial correlation with geographic distance, it remains statistically significant. This implies that old neighbours play an additional role in influencing banks' entry. I attribute the effects to the existing lending relationships.

Columns (3) and (4) present results on entry likelihood ten years after deregulation. The coefficients for *Old Neighbours* remain positive and statistically significant. In column (4), for instance, the estimated value is 2.72, which suggests that a one-standard-deviation increase (i.e., 10.1 percentage points) in share of old neighbours increases the probability of entry in ten years by 27.2 basis point, more than one third of the unconditional mean (75 bp). These findings indicate that the presence of old neighbours has a lasting impact on banks' expansion decisions.

5.5 Heterogeneous effects

To shed light on relationship channel underlying the effects of old neighbours, I examine the heterogeneous effects by banks' lending specialisations. Banks with a greater focus on commercial and industrial (C&I) lending are more likely to serve firms, and thus the identity of firms in newly accessible markets matters more for these institutions. To test this hypothesis, I re-estimate the model in Equation 4 and include an interaction term between *Old Neighbours* and the share of commercial and industrial loans in the bank's asset portfolio, *C&I Loan*.

The results presented in Table 4 confirm the previous conjecture. The coefficients associated with the interaction between *Old Neighbours* and *C&I Loan* are positive and statistically significant, indicating that the effects of old neighbours are stronger for banks concentrating in commercial lending businesses. Moreover, the coefficients on the non-interaction term *Old Neighbours* are now close to zero and statistically insignificant. This suggests that if a bank does not have corporate lending businesses (i.e., *C&I Loan* = 0), then the presence of old neighbouring firms becomes irrelevant for entry decisions.

These findings are consistent with effects of old neighbours being driven by pre-existing lending relationships.

5.6 Placebo tests

To provide evidence that entry is genuinely constrained before deregulation, and thus that expansion is limited despite the presence of old neighbours elsewhere, I conduct placebo tests using the same specification but predicting banks' entry into states that would remain regulated within a specified time frame. For example, for a placebo test with a two-year horizon, I pick out state pairs where a home state would remain regulated within the next two years for each year between 1982 and 1992. Specifically, in year 1982, state pairs (ordered as home-foreign) such as Arizona-California are included in the sample, since banks in California were still prohibited from entering Arizona in 1984. However, state pairs like California-Arizona are excluded, as they would be deregulated in 1984 and banks in Arizona were permitted to enter California. I then associate banks in California to counties in Arizona, and predict their entry as if they were deregulated. For the ten-year horizon, it is only possible to designate placebo deregulation in years 1982–1984, because, starting in 1985, all state pairs would be fully deregulated within the next ten years.

The results of the placebo tests are presented in Table 5. The reported coefficients on *Old Neighbours* are scaled up by 10^4, thus the effects are essentially zero, and moreover they are statistically insignificant. This suggests that the presence of old neighbours do not predict entry under regulation, and that banks' geographic expansion shown previously is indeed a result of deregulation.

6 Lending in Deregulated Markets

I now turn to investigation of lending outcomes in the deregulated regions. An important objective of deregulating the banking sector to encourage entry of non-local banks is to provide additional financial support for local economic activities. As the presence of old neighbouring firms influence a bank's location choice, and the physical proximity between bank branches and borrowers is essential for credit provision, it is reasonable to expect that the geographic distribution of credits in the deregulated regions would reflect these factors. In this section, I demonstrate that banks increase their lending in the new markets after deregulation, and more so to locations with a stronger presence of old neighbours.

6.1 Measuring lending volumes

I start by constructing measures of lending volumes across geographic locations. To do so, I will use an extended sample of corporate loans from the merged DealScan-D&B dataset spanning the period 1987–2005, and I will construct two measures of loan volumes at the bank-county level: the dollar amount of loans and the number of loans. However, two complexities arise: (1) a single loan deal often involves multiple lenders, and (2) the borrowing firm may have operations in multiple locations. To address these issues, I take the following approach.

To assign a dollar amount of the loan to the bank-county level, I first allocate the loan deal amount across lenders based on (imputed) lender shares, and then further distribute each lender's share across counties based on the distribution of the firm's employment across these locations.[5] Consider an example where a firm borrows \$10 million from banks B_1 and B_2 with lender shares of 60% and 40%, respectively. The firm operates in counties C_1 and C_2 where 90% and 10% of its employment is located, respectively. In this scenario, the dollar amount of lending by bank B_1 associated with county C_1 is assigned \$5.4$(= 10 \times .6 \times .9)$ million, and similar calculations can be made for other allocations, as shown in Table 6.

To compute the number of loans at the bank-county level, I simply assign the lender's share of the loan to each county where the borrower operates. In the previous example (Table 6), the number of loans made by bank B_1 to county C_1 is thus equal to 0.6, representing

[5] Following Chodorow-Reich (2014), missing values of lender shares are imputed based on the average of other loans with similar syndicate structure (same number of lead and participant lenders).

the lender share of bank B_1 in this loan contract.

Note that the proposed measures of lending volumes above do not necessarily capture where the funds are ultimately invested, as we do not observe how firms internally allocate these funds across establishments. Nonetheless, these measures reflect the geographic distribution of the firms receiving credit, which aligns with the primary focus of the current study.

6.2 Effects of old neighbours

I now examine how lending outcomes evolve in the deregulated markets, and whether the presence of old neighbouring firms affects these outcomes.

First, I examine the average credit growth across counties within the deregulated states. To do so, I estimate the following specification:

$$Loan_{bct} = \phi_{bt} + \phi_{ct} + \sum_{k \neq -1} \beta_k \times \mathbb{I}\{YsD_{bct} = k\} + \varepsilon_{bct}, \tag{7}$$

where the dependent variable $Loan_{bct}$ is either the logarithm of one plus the dollar amount of loans or the logarithm of one plus the number of loans by bank b in county c in calendar year t. The main explanatory variable of interest is the dummy variables $\mathbb{I}\{YsD_{bct} = k\}$ where YsD stands for number of years since deregulation. Thus, the coefficients β_k's measure the change in lending volumes relative to the year prior to the deregulation. Finally, ϕ_{bt} and ϕ_{ct} are bank-year and county-year fixed effects that absorb credit supply and demand shocks at the bank- and county- levels. The sample include all bank-county pairs that were affected by the interstate banking deregulation during 1982–1995. And I trace the lending outcomes from 5 years prior to the deregulation to 10 years after, whenever possible.

Figure 9 plots the coefficient estimates β_k's. The figure shows that credit growth was negligible before deregulation, but substantial after deregulation. Table 7 performs a formal test on the change in credit growth rate by fitting different linear time trends before and after the deregulation:

$$Loan_{bct} = \phi_{bt} + \phi_{ct} + \beta_1 YsD_{bct} + \beta_2 YsD_{bct} \times Post_{bct} + \varepsilon_{bct}, \tag{8}$$

where $Post_{bct}$ is an indicator for years after deregulation, i.e., when $YsD_{bct} \geq 0$. Thus, the coefficient β_1 estimates the average annual growth rate during the five years before deregulation, and β_2 estimates the change in growth rate after deregulation. The results in Table 7 show that the coefficient on the interaction term $YsD_{bct} \times Post_{bct}$ is positive and statistically significant, which suggests that credit growth accelerates since deregulation, consistent with the notion that entry is essential for credit provision.

Second, I examine whether the presence of old neighbouring firms affects credit growth across locations. I include the interaction between the year-since-deregulation dummies with the measure of information barrier *Old Neighbours* in Equation 7 as follows:

$$\begin{aligned} Loan_{bct} = \sum_{k \neq -1} \beta_{1,k} \times \mathbb{I}\{YsD_{bct} = k\} + \sum_{k} \beta_{2,k} \left[Old\ Neighbours\right]_{bc} \times \mathbb{I}\{YsD_{bct} = k\} \\ + \gamma' X_{bct} + \phi_{bt} + \phi_{ct} + \varepsilon_{bct}, \end{aligned} \tag{9}$$

where the dependant variable $Loan_{bct}$ is again the loan volume by bank b to county c in calendar year t. X_{bct} include interactions of the *YsD* dummies with the geographic distance between the bank and the county to control for the time varying effects of distance on lending outcomes. ϕ_{bt} and ϕ_{ct} represent bank-year and county-year fixed effects. The coefficients of interests are $\beta_{2,k}$'s, which capture the evolution of the difference in lending volumes across counties with different degrees of presence of the bank's old neighbours.

Figure 10 plots the coefficient estimates $\beta_{2,k}$. These estimates are positive prior to the deregulation because banks have been lending to their neighbouring firms that also operate in the later deregulated states, and thus counties with higher concentration of old neighbouring firms should have higher lending volumes even prior to the deregulation. More importantly, since the deregulation, the coefficients are becoming larger and have been doing so faster, which suggests that lending increases by more and faster in counties with stronger presence of old neighbours. I formally test these statements using the following specifications:

$$\begin{aligned} Loan_{bct} = \beta_1 \left[Old\ Neighbours\right]_{bc} + \beta_2 \left[Old\ Neighbours\right]_{bc} \times Post_{bct} \\ + \gamma' X_{bct} + \phi_{YsD(bct)} + \phi_{bt} + \phi_{ct} + \varepsilon_{bct}, \end{aligned} \tag{10}$$

where the coefficient β_1 measures the gap of credit volumes between locations with higher and lower shares of old neighbours prior to the deregulation, and the coefficient β_2 measures the change in this lending gap after the deregulation, and

$$Loan_{bct} = \beta_1 [Old\ Neighbours]_{bc} \times YsD_{bct} + \beta_2 [Old\ Neighbours]_{bc} \times YsD_{bct} \times Post_{bct} + \gamma' X_{bct} + \phi_{YsD(bct)} + \phi_{bt} + \phi_{ct} + \varepsilon_{bct}, \tag{11}$$

where the coefficient β_1 measures the difference in credit growth rates between locations with higher and lower shares of old neighbours prior to the deregulation, and the coefficient β_2 measures the change in this growth rate gap after the deregulation. Table 8 reports the results from the above two regressions. Columns (1) and (3) suggest that credit volumes are higher in counties with more old neighbours before deregulation, and even higher after. Columns (2) and (4) suggest that credit growth rates are higher in counties with more old neighbours, and even higher after the deregulation.

Finally, I examine whether the increasing lending gap is driven by lendings to firms operating in the original neighbourhood, or those outside the original neighbourhood. To answer this question, I estimate Equation 9 separately for lendings to firms in and outside the bank's old neighbourhood. Panels A and B in Figure 11 plots the difference in credit volumes to firms in the banks' old neighbourhood between counties with lower and higher shares of old neighbours. The coefficients on the variable *Old Neighbours* are naturally positive prior to the deregulation, as banks lend more to neighbouring firms, places with more old neighbouring firms will be allocated more loans. More importantly, the coefficient keeps increasing after the deregulation, which suggests that the growth in lending to firms operating in the original neighbourhood contribute to the increasing gap in credit volumes between deregulated counties wigh higher and lower shares of old neighbours. Panel A of Table 9 performs a formal tests on the change in both the level and growth rate of lending volumes to firms operating in the bank's original neighbourhood before and after the deregulation, similar to Equations 10 and 11. The positive and statistically significant coefficients on *Old Neighbours* in columns (1) and (3) suggest that, prior to the deregulation, lendings to firms operating in the original neighbourhood are higher in counties with higher concentration of old neighbours. The positive and statistically significant coefficients on the variable *Old Neighbours* $\times$ *Post* suggest that this lending gap becomes even larger after the deregulation. Columns (2) and (4) show that the growth rate of lending to firms in the original neighbourhood is (weakly) higher after the deregulation than before.

In terms of lendings to firms operating outside the bank's original neighbourhood, Panels C and D in Figure 11 shows the lending gap between counties with higher and lower shares of old neighbours. Prior to the deregulation, the lending gap is naturally negative because borrowers outside the bank's original neighbourhood are most likely operating in counties with lower concentration of old neighbours. Interestingly, this gap starts to shrink after deregulation and eventually becomes significantly positive, suggesting that firms being financed outside the bank's original neighbourhood are now more likely to operate in counties with a higher share of old neighbours. This is consistent with notion that the presence of old neighbours facilitates entry after deregulation, and entry brings credits for local businesses. Panel B of Table 9 performs the tests based on Equations 10 and 11 where the outcomes are now loan volumes to firms outside the bank's original neighbourhood. The negative coefficients on *Old Neighbours* in columns (1) and (3) suggest that lendings to these firms are lower in counties with higher concentration of old neighbours prior to the deregulation. And the positive and statistically significant coefficients on the interaction term *Old Neighbours* × *Post* suggest that the lending gap is reversed after the deregulation. Columns (2) and (4) show that the coefficients on *Old Neighbours* × *YsD* are close to zero and statistically insignificant, suggesting that there is no significant difference in the lending growth between counties with higher or lower shares of old neighbours before deregulation. The coefficients on *Old Neighbours* × *YsD* × *Post* are positive and statistically significant, which suggests that, after the deregulation, lending grows faster in counties with a stronger presence of old neighbour.

In summary, the results above suggest that banks increase their lending in the deregulated markets after deregulation, and more so to locations with a stronger presence of old neighbours. This pattern is observed for lendings to firms both inside and outside the bank's original neighbourhood, highlighting the significant role of old neighbours in facilitating entry and credit provision in the new markets.

7 Employment Effects

In this section, I examine how the presence of banks' old neighbouring firms affect real economic outcomes following banking deregulation. For each county in the deregulated state, I aggregate the measure of old neighbours across all potential entrant banks. Then I compare employment outcomes across counties within each deregulated state using a stacked difference-in-differences design.

For each county c, the aggregate presence of old neighbouring firms is defined as:

$$AggOldNbour_c = \sum_b \left[Old\ Neighbours\right]_{bc}, \tag{12}$$

where the summation is across all candidate banks across the country that can potentially enter county c after the state's full deregulation, and the share of old neighbours is measured in the year prior to the state's first deregulation event.

I trace the employment levels from 5 years before the first deregulation to 15 years after for each county, and stack observations of all states using this common time window. Employment data is sourced from County Business Patterns. I then estimate the following specification:

$$Emp_{ct} = \alpha_{st} + \alpha_c + \sum_{k=-5}^{15} \beta_k \left[AggOldNbours\right]_c \times \mathbb{1}\{t = k\} + \gamma X_{ct} + \varepsilon_{ct}, \tag{13}$$

where the time index t represents the number of years since first deregulation; the dependent variable Emp_{ct} is the employment level in county c, t years since first deregulation; α_{st} represent state-time fixed effects; α_c are county fixed effects; X_{ct} include interactions of time dummies with with the pre-deregulation employment level. Coefficients β_k thus estimate the dynamic effects of the presence of old neighbours on employment relative to the pre-deregulation level. Figure 12 plots the coefficients estimates of β_k. After the deregulation, employment is higher in counties with a higher share of old neighbours. The estimates suggest that a 100% increase in the aggregate share of old neighbouring firms adds 150 more employees for the county, 10 years after first deregulation.

8 Conclusions

In this paper, I show that the spatial distribution of firms shapes banks' geographic expansion following deregulation. Evidence from the U.S. interstate banking deregulation suggests that banks are more likely to enter new locations with greater presence of familiar firms from their original neighbourhood. The effects are stronger for banks concentrating in commercial lending businesses, consistent with the results being driven by pre-existing lending relationships. Furthermore, firms in locations with higher share of old neighbours of non-local banks receive more credits and experience stronger employment growth. These findings highlight the distributional impacts of banking deregulation as shaped by historical bank-firm connections.

These findings carry important policy implications for financial liberalisation and local economic development, many of which warrant further investigations. First, they highlight that relaxing geographic restrictions does not guarantee uniform entry across regions: pre-existing economic linkages appear to shape where banks expand, potentially limiting the reach of deregulation. Second, the fact that the presence of old neighbours affect entry and credit provision implies that local firms, especially small businesses, may not fully benefit from the increased competition if they are not connected to the entrant banks or located close to those who are. This could potentially exacerbate existing inequalities in credit access. Third, while geographic expansion is often expected to enhance diversification, the observed tendency for banks to expand into locations with familiar firms indicates that diversification gains may be more limited than anticipated. The balance between specialisation and diversification of the banking sector thus bears attention from both researchers and policymakers.

References

Amel, D. F. (1993). State laws affecting the geographic expansion of commercial banks. *Federal Reserve Board*.

Bofondi, M. and Gobbi, G. (2006). Informational barriers to entry into credit markets. *Review of Finance*, 10(1):39–67.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics*, 129(1):1–59.

Greenstone, M., Mas, A., and Nguyen, H.-L. (2020). Do credit market shocks affect the real economy? Quasi-experimental evidence from the great recession and "normal" economic times. *American Economic Journal: Economic Policy*, 12(1):200–225.

Huber, K. (2018). Disentangling the effects of a banking crisis: Evidence from german firms and counties. *American Economic Review*, 108(3):868–898.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3):639–670.

Mian, A. (2006). Distance constraints: The limits of foreign lending in poor economies. *The Journal of Finance*, 61(3):1465–1505.

Nguyen, H.-L. Q. (2019). Are credit markets still local? Evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1):1–32.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. *The Journal of Finance*, 57(6):2533–2570.

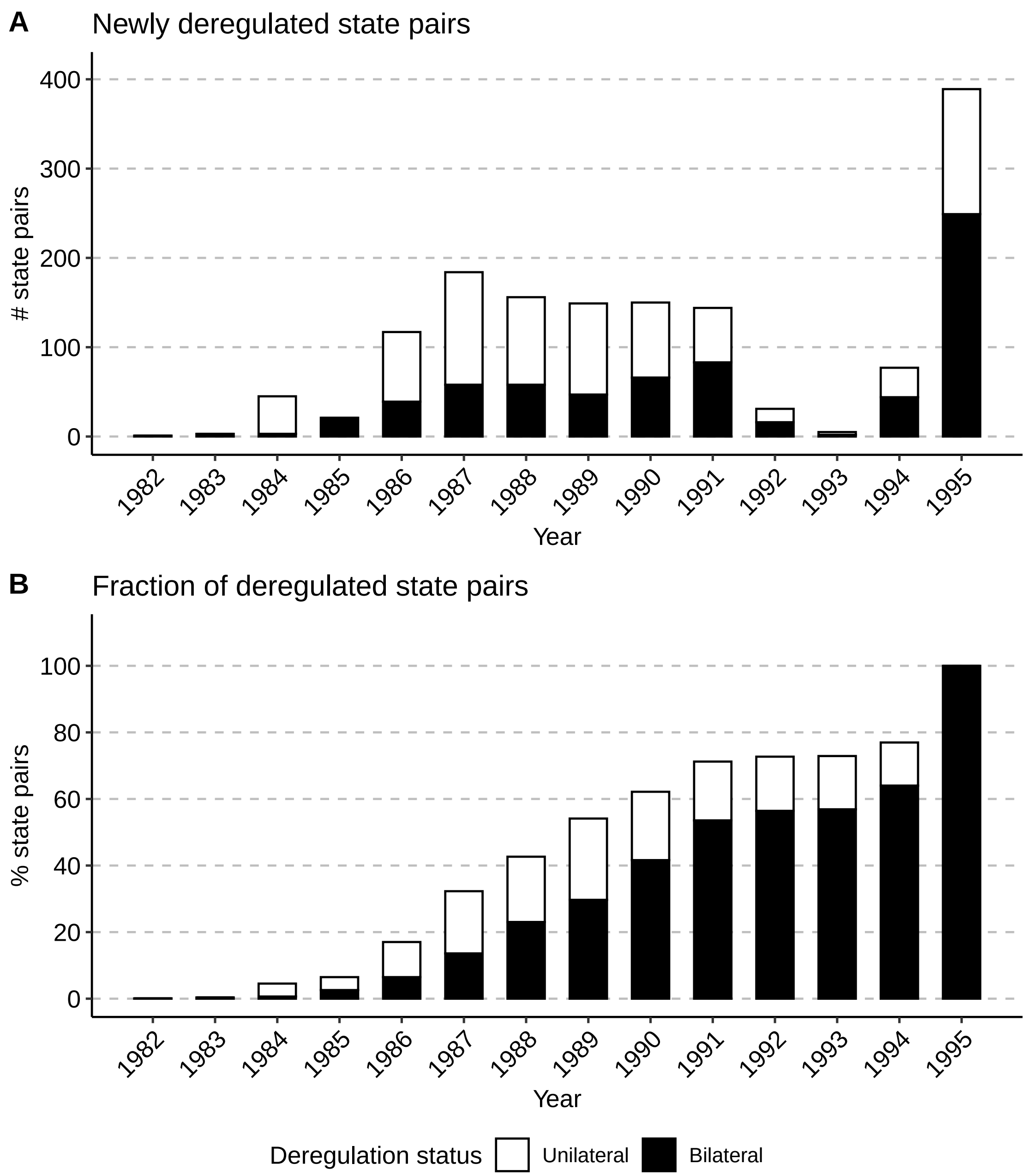

Figure 1: Evolution of Interstate Banking Deregulation

Notes: This figure plots the evolution of interstate banking deregulation. Panel A shows the number of newly deregulated state pairs in each year. The deregulation status of each pair is classified as unilateral if only one state permitted entry of BHCs from the other in that year, and as bilateral if both states allowed entry of BHCs from each other. Panel B shows the cumulative fraction of deregulated state pairs. The deregulation status of each pair is classified as unilateral if only one state has permitted entry of BHCs from the other by the end of the year, and as bilateral if both states have permitted entry from each other. The sample includes 47 contiguous states (i.e., Alaska, Delaware, Hawaii and South Dakota are excluded) and thus 1081 (= $47 \times 46/2$) state pairs in total.

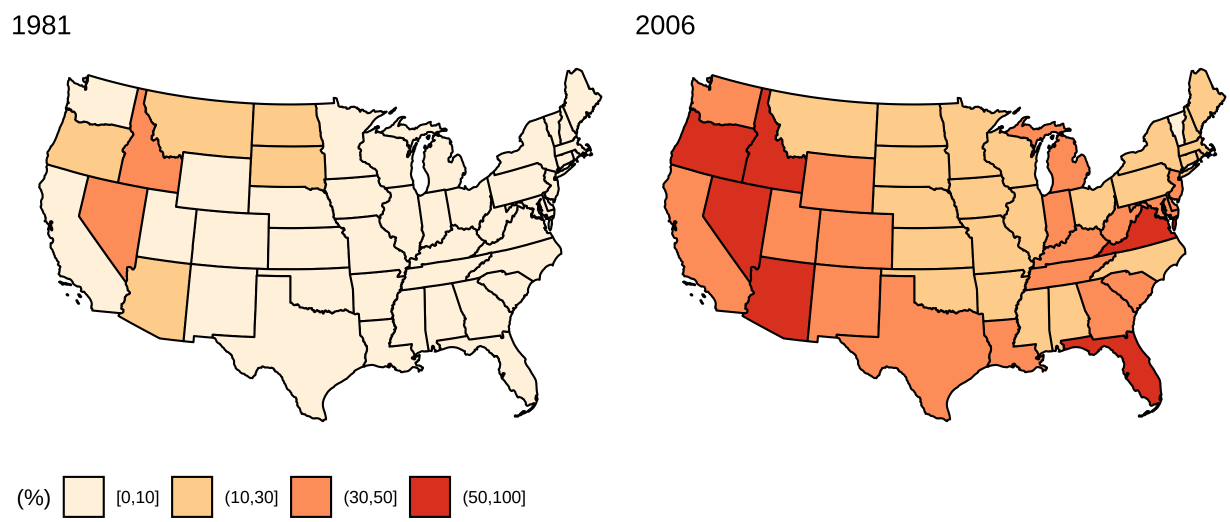

Figure 2: Share of Branches by Out-of-State BHCs

Notes: This figure plots the share of branches controlled by out-of-state BHCs in 1981 versus 2006. Source: Summary of Deposits.

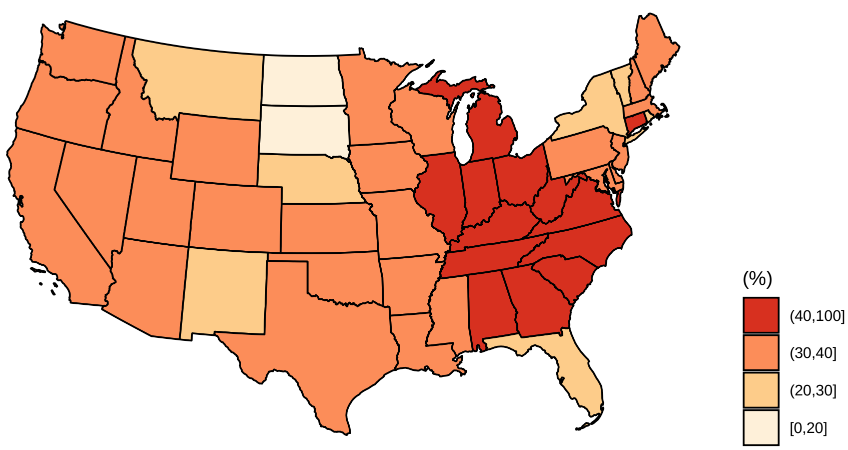

Figure 3: Employment Share of Multistate Firms

Notes: This figure plots the employment share in each state and county by large multistate firms in 1980. Source: Dun & Bradstreet.

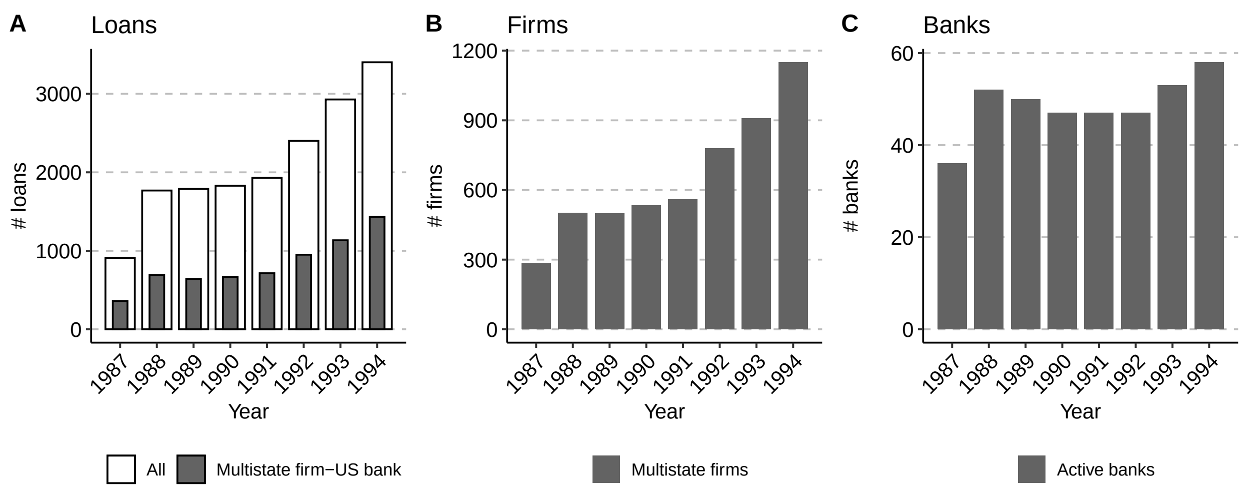

Figure 4: Lending Relationship Sample

Notes: This figure plots the number of loans and unique borrowers and lenders used to investigate lending relationships. Panel A plots the total number of loans in DealScan to US borrowers. The grey portion represents the fraction of loans for which the borrower can be matched to Dun & Bradstreet and its ultimate parent is a non-financial or non-government firm operating in multiple states. Panel B plots the number of unique firms, and Panel C the number of active lenders (appear on more than 10 loans).

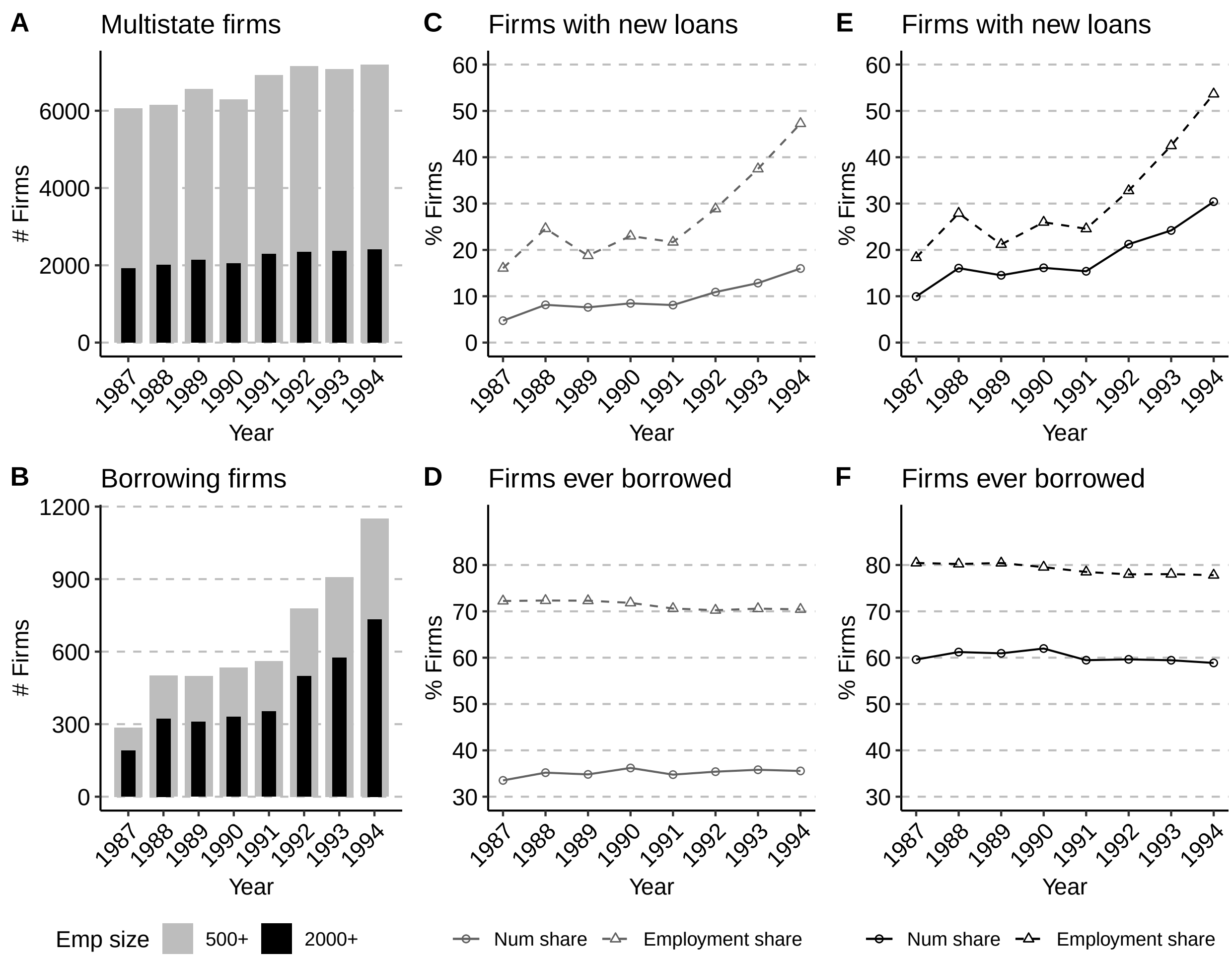

Figure 5: Bank Dependence of Multistate Firms

Notes: This figure examines the coverage of multistate firms by DealScan borrowers. Panel A plots the number of total number of multistate firms categorised by employment size. Panel B plots the number of firms in DealScan. Panels C and D show the fraction among all multisate firms with more than 500 employees that borrowed in any given year, or ever borrowed during the sample period. Panels E and F show the fraction among all multisate firms with more than 2000 employees that borrowed in any given year, or ever borrowed during the sample period.

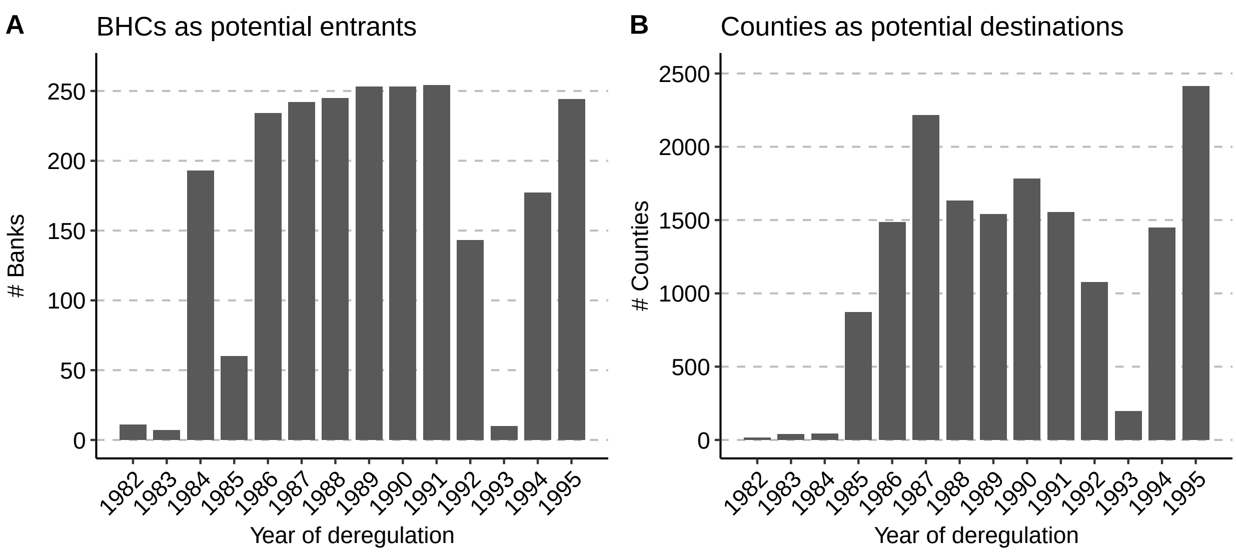

Figure 6: Bank Entry Sample

Notes: This figure plots the number of potential entrant banks and potential desitnation counties that are affected by the deregulation in each year. Potential entrant banks are banks that have not entered the deregulated states at the time of deregulation, that have ever had at least one billion deposits and that have ever expanded across state borders during the sample period (1982–2005). Potential destination counties are all counties in the deregulated states. Note that not all banks are paired with all counties displayed in this figure for the entry analysis, only those affected by the deregulation are included.

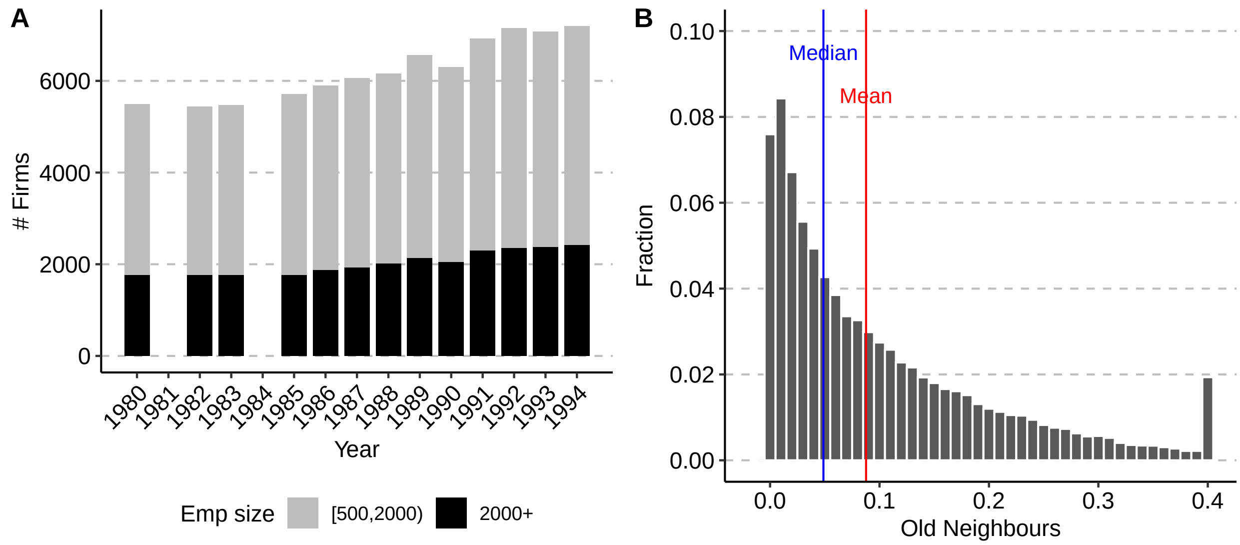

Figure 7: Multistate Firms and Distribution of Old Neighbours

Notes: Panel A plots the number of large multistate nonfinancial firms used to construct variable *Old Neighbours*. Panel B plots the distribution of variable *Old Neighbours* across bank-county pairs. For illustrative purpose, values of zero are omitted from the figure (around 15% of the observations), but are included in the calculation of the mean and median). The last bin contains all values greater than 0.4.

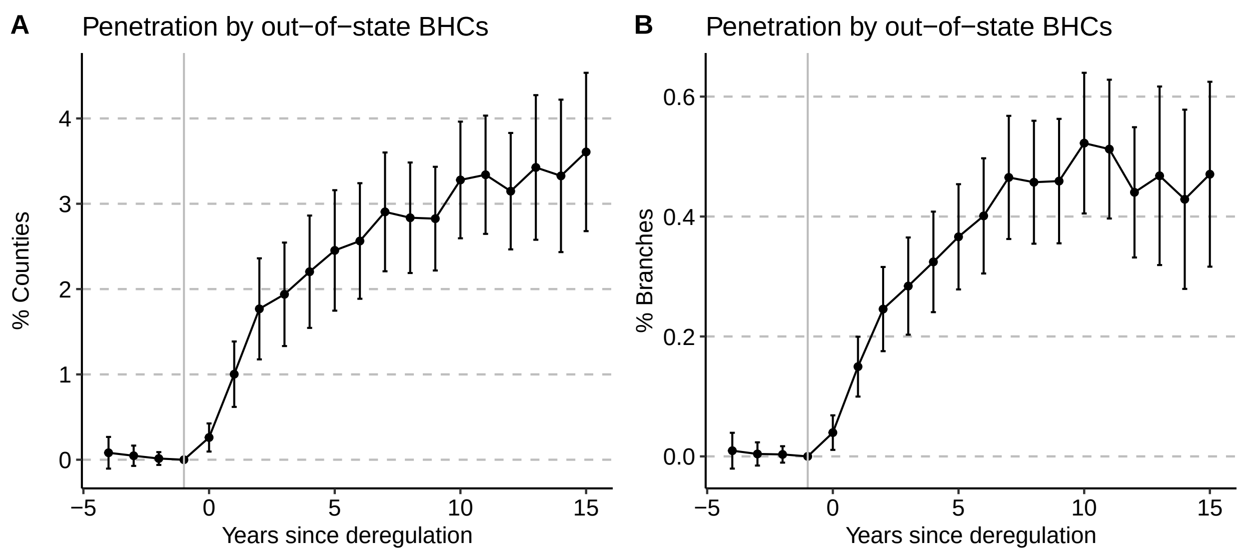

Figure 8: Speed of Entry

Notes: This figure plots the coefficients from Equation 6. The dependent variable $FrgnBHCShare_{ijh}$ is the penetration rate of home state i by banks in foreign state j, h years since the deregulations. Panel A measures the penetration rate by the share of counties entered by foreign banks, while Panel B measures the penetration rate by the share of branches owned by foreign banks. The error bars indicate 95% confidence intervals, with standard errors clustered at home-foreign state pair level.

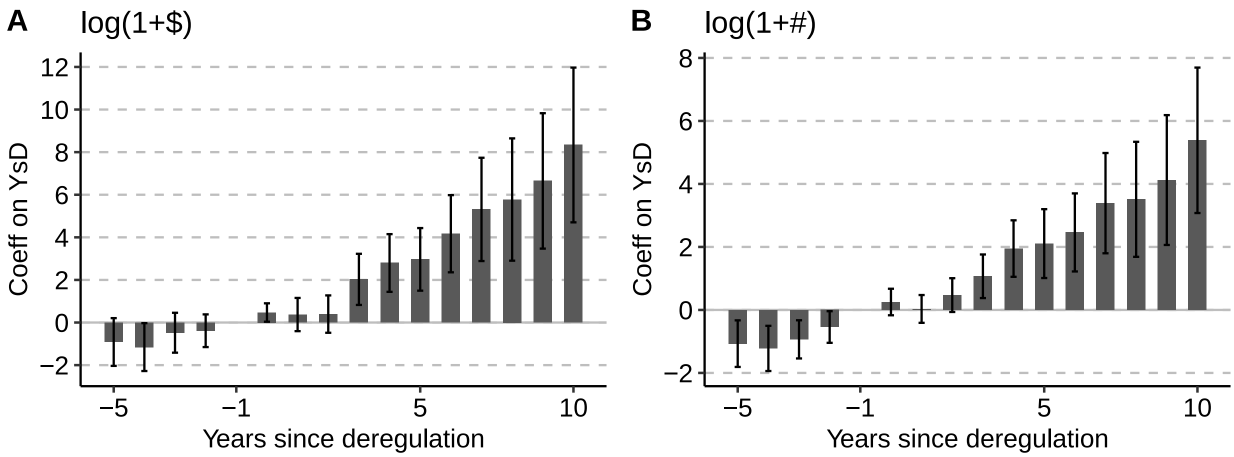

Figure 9: Corporate Lending Growth in Deregulated Counties

Notes: This figure plots the coefficient estimates from Equation 7. The dependent varible in Panel A is the logarithm of one plus the dollar amount of loans. The dependent varible in Panel B is the logarithm of one plus the number of loans. Standard errors are clustered at the bank and county levels. The error bars represent 95% confidence intervals.

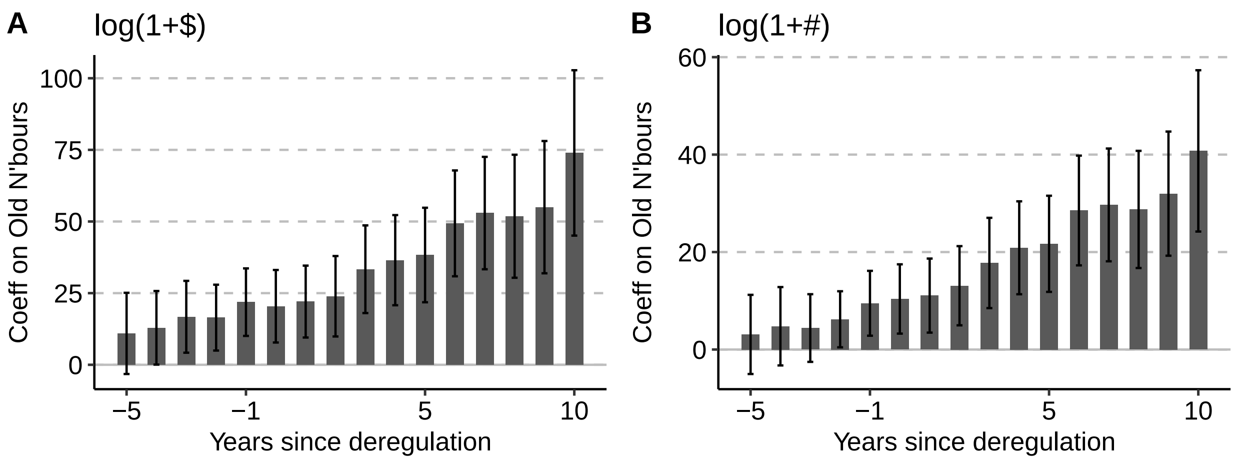

Figure 10: Old Neighbours and Corporate Lending Growth

Notes: This figure plots the coefficient estimates from Equation 9. The dependent variable in Panel A is the logarithm of one plus the dollar amount of loans. The dependent variable in Panel B is the logarithm of one plus the number of loans. Standard errors are clustered at the bank and county levels. The error bars represent 95% confidence intervals.

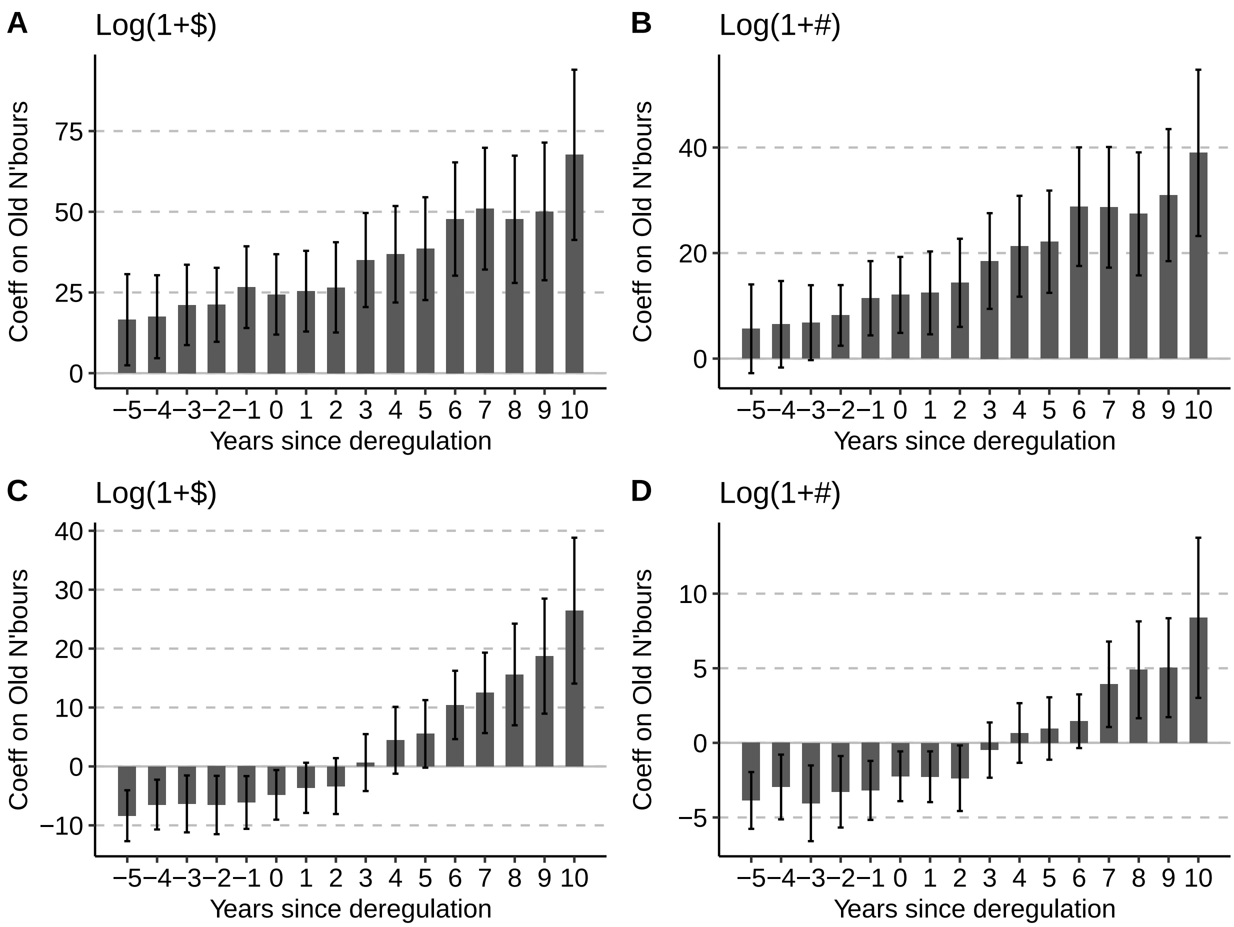

Figure 11: Lending to Firms In or Outside Old Neighbourhoods

Notes: This figure plots the coefficient estimates from Equation 9. Panels A and B plot the effects on lending to firms in the old neighbourhood. Panels C and D plot the effects on lending to firms outside the old neighbourhood. The dependent variables in Panels A and C are the logarithm of one plus the dollar amount of loans. The dependent variables in Panels B and D are the logarithm of one plus the number of loans. Standard errors are clustered at the bank and county levels. The error bars represent 95% confidence intervals.

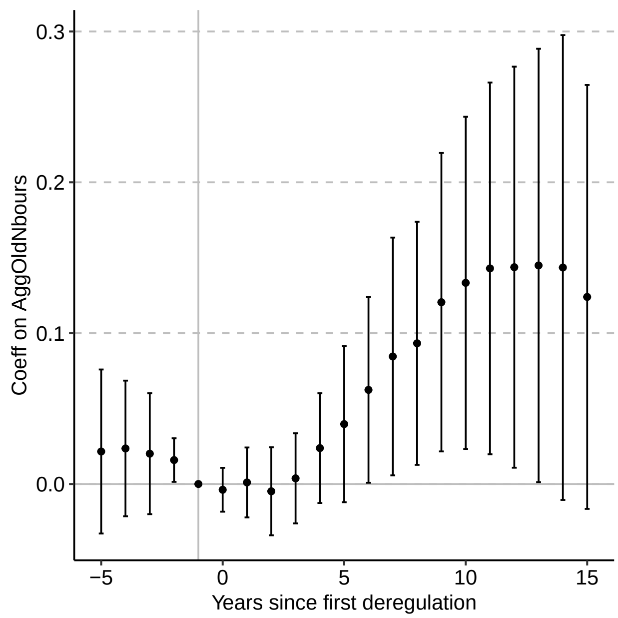

Figure 12: Employment Effects

Notes: This figure plots the effects of old neighbours on employment estimated from Equation 13.

Table 1: Lending Relationships between Neighbours

	(1) Loan	(2) Loan
Neighbour	8.14***	4.02***
	(1.61)	(0.417)
Firm-Year FE		Yes
Bank-Year FE		Yes
Mean of Dep Var	7.97	7.97
R^2 Adj	0.022	0.227
Observations	268,017	268,017

Notes: This table reports regression results from Equation 1. The dependent variable *Loan* is an indicator for whether a firm borrows from a bank, multiplied by 100. The explanatory variable *Neighbour* is an indicator for whether the firm and bank operate in the same county. Standard errors are double clustered at firm and bank levels. Significance levels: ***1%, **5%, *10%.

Table 2: Lending Relationships are Persistent

	(1)	(2)
	Loan	Loan
Previous	55.7***	48.3***
	(2.32)	(1.55)
Firm-Year FE		Yes
Bank-Year FE		Yes
Mean of Dep Var	8.34	8.34
R^2 Adj	0.285	0.384
Observations	96,435	96,435

Notes: This table reports regression results from Equation 3. The dependent variable *Loan* is an indicator for whether a firm borrows from a bank, multiplied by 100. The explanatory variable *Neighbour* is an indicator for whether the firm and bank operate in the same county. Standard errors are clustered at firm and bank levels. Significance levels: ***1%, **5%, *10%.

Table 3: Old Neighbours and Bank Entry

	(1)	(2)	(3)	(4)
	Entry_{+2}	Entry_{+2}	Entry_{+10}	Entry_{+10}
Old Neighbours	1.15***	0.926***	3.39***	2.72***
	(0.28)	(0.266)	(0.71)	(0.668)
LogDist		−0.748***		−2.02***
		(0.168)		(0.329)
Bank-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Mean of Dep Var (%)	0.19	0.19	0.75	0.75
R^2 Adj	0.144	0.146	0.237	0.242
Observations	653,257	653,257	442,097	442,097

Notes: This table reports regression results from Equation 4. The dependent variable $Entry_{+h}$ is an indicator for whether bank controls a branch in the destination county, h years after deregulation. Variable *Old Neighbours* is the employment share in the destination county of a bank's original neighbouring firms, divided by 100. Variable *LogDist* is the log geodesic distance between the bank's headquarters and the destination county (in miles), divided by 100. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Table 4: Old Neighbours and Bank Entry: Heterogeneity

	(1) Entry_{+2}	(2) Entry_{+10}
Old Neighbours	0.00326	−1.06
	(0.298)	(0.883)
Old Neighbours × C&I Loan	6.05**	25.1***
	(2.59)	(8.62)
LogDist	−0.75***	−2.03***
	(0.168)	(0.329)
Bank-Year FE	Yes	Yes
County-Year FE	Yes	Yes
Mean of Dep Var (%)	0.19	0.75
R^2 Adj	0.146	0.242
Observations	653,241	442,097

Notes: This table reports regression results from Equation 4, allowing effect heterogeneity across bank characteristics. The dependent variable $Entry_{+h}$ is an indicator for whether the bank controls a branch in the destination county, h years after deregulation. Variable *Old Neighbours* is the employment share in the destination county by the bank's original neighbouring firms. Variable *C&I Loan* is the share of assets invested in commercial and industrial loans. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Table 5: Old Neighbours and Bank Entry: Placebo Tests

	(1) Entry_{+2}	(2) Entry_{+10}
Old Neighbours	2.81	−4.50
	(2.04)	(3.32)
LogDist	−3.93	−9.26
	(2.70)	(6.81)
Bank-Year FE	Yes	Yes
County-Year FE	Yes	Yes
Mean of Dep Var (bp)	1.3	3.1
R^2 Adj	0.011	0.037
Observations	4,235,481	461,116

Notes: This table reports results from placebo tests of bank entry model in Equation 4. The dependent variable $Entry_{+h}$ is an indicator for whether bank controls a branch in the destination county, h years after deregulation. Variable *Old Neighbours* is the employment share in the destination county of a bank's original neighbouring firms, divided by 10^4. Variable *LogDist* is the log geodesic distance between the bank's headquarters and the destination county, divided by 10^4. Standard errors are clustered at bank and county levels. Significant level: ***1%, **5%, *10%.

Table 6: Allocation of Loans to Bank-County Level

Bank	County	# Loans	$M Loans
B_1	C_1	0.6	$5.4(= 10 \times .6 \times .9)$
B_1	C_2	0.6	$0.6(= 10 \times .6 \times .1)$
B_2	C_1	0.4	$0.4(= 10 \times .4 \times .1)$
B_2	C_2	0.4	$0.4(= 10 \times .4 \times .1)$

Notes: This table demonstrates how each loan in DealScan is allocated to the bank-county level. The calculation is based on the following numerical example: a firm borrows $10M from banks B_1 and B_2 with 60% and 40% lender shares respectively, and the firm operates establishments in counties C_1 and C_2 with 90% and 10% of its total employment respectively.

Table 7: Deregulation and Corporate Lending Growth

	(1) Log(1+$)	(2) Log(1+#)
YsD	0.11	0.20^{**}
	(0.12)	(0.087)
YsD×Post	0.66^{***}	0.29^{**}
	(0.20)	(0.120)
Bank-Year FE	Yes	Yes
County-Year FE	Yes	Yes
R^2 Adj	0.45	0.55
Observations	2,526,679	2,526,679

Notes: This table reports the regression results from Equation 8. The sample includes obvervations at bank-county-year level from 5 years before deregulation to 10 years after. The dependent variables are lending volumes measured by either the logarithm of one plus the dollar amount of loans or logarithm of one plus the number of loans. Variable *YsD* is the number of years since deregulation. Variable *Post* is an indicator for years after deregulation, i.e., when $YsD \geq 0$. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Table 8: Old Neighbours and Corporate Lending Growth

	(1) Log(1+$)	(2) Log(1+$)	(3) Log(1+#)	(4) Log(1+#)
Old N'bours	20.47***	18.30***	8.37**	9.04**
	(5.78)	(6.37)	(3.23)	(3.85)
Old N'bours×Post	19.30***		13.75***	
	(5.00)		(3.07)	
Old N'bours×YsD		1.08		1.20*
		(1.22)		(0.70)
Old N'bours×YsD×Post		3.62**		1.62
		(1.75)		(0.99)
Bank-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
YsD FE	Yes	Yes	Yes	Yes
Dist Cntrl	Yes	Yes	Yes	Yes
R^2 Adj	0.46	0.46	0.56	0.56
Observations	2,526,679	2,526,679	2,526,679	2,526,679

Notes: This table reports the regression results from Equations 10 and 11. The sample includes obvervations at bank-county-year level from 5 years before deregulation to 10 years after. The dependent variables are lending volumes measured by either the logarithm of one plus the dollar amount of loans or logarithm of one plus the number of loans. Variable *Old N'bours* is the employment share in the destination county of a bank's old neighbouring firms. Variable *YsD* is the number of years since deregulation. Variable *Post* is an indicator for years after deregulation, i.e., when $YsD \geq 0$. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Table 9: Lending to Firms In or Outside the Old Neighbourhoods

Panel A: Firms in the old neighbourhoods				
	(1)	(2)	(3)	(4)
	Log(1+$)	Log(1+$)	Log(1+#)	Log(1+#)
Old N'bours	24.38^{***}	22.83^{***}	10.16^{***}	10.88^{***}
	(5.90)	(6.34)	(3.32)	(3.93)
Old N'bours×Post	15.12^{***}		12.16^{***}	
	(4.49)		(2.92)	
Old N'bours×YsD		0.98		1.11^{*}
		(1.11)		(0.66)
Old N'bours×YsD×Post		2.69^{*}		1.37
		(1.52)		(0.90)
Panel B: Firms outside the old neighbourhoods				
	(1)	(2)	(3)	(4)
	Log(1+$)	Log(1+$)	Log(1+#)	Log(1+#)
Old N'bours	-4.17^{**}	-7.22^{***}	-2.57^{***}	-3.47^{***}
	(1.94)	(2.43)	(0.91)	(1.07)
Old N'bours×Post	10.64^{***}		3.87^{***}	
	(2.51)		(1.09)	
Old N'bours×YsD		−0.07		0.02
		(0.45)		(0.16)
Old N'bours×YsD×Post		3.02^{***}		1.00^{***}
		(0.87)		(0.34)
Bank-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
YsD FE	Yes	Yes	Yes	Yes
Dist Cntrl	Yes	Yes	Yes	Yes
Observations	2,526,679	2,526,679	2,526,679	2,526,679

Notes: This table reports the regression results from Equations 10 and 11 separately for lendings to firms in and outside the banks' old neighbourhoods. The sample includes observations at bank-county-year level from 5 years before deregulation to 10 years after. The dependent variables are lending volumes measured by either the logarithm of one plus the dollar amount of loans or logarithm of one plus the number of loans. Variable *Old N'bours* is the employment share in the destination county of a bank's old neighbouring firms. Variable *YsD* is the number of years since deregulation. Variable *Post* is an indicator for years after deregulation, i.e., when $YsD \geq 0$. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Internet Appendix

A Chronology of Interstate Banking Deregulation

In this section, I present the chronology of interstate banking deregulation constructed based on Amel (1993)[6]. In Table A.1 below, each record contains information on the year of deregulation, the home state which opens the banking sector, and the list of foreign states whose BHCs are allowed to expand. The year of deregulation is the year in which the entry of out-of-state BHCs became effective, taking into account the reciprocity requirements set forth by the relevant legislations. For example, the state of Maine deregulated in 1978 with reciprocity requirement, while New York, the second deregulated state, only passed a similar law in 1982, which made Maine's deregulation effective in 1982, as shown by the first record in the table below. I include only 47 contiguous states (excluding Alaska, Hawaii, Delaware and South Dakota). A value "All" for FOREIGN column indicates that the home state is open to all other states.

Table A.1: Chronology of Interstate Banking Deregulation

NO	YEAR	HOME	FOREIGN
1	1982	ME	NY
2	1982	NY	ME
3	1983	CT	MA, ME
4	1983	MA	CT, ME
5	1983	ME	CT, MA
6	1984	CT	RI
7	1984	MA	RI
8	1984	ME	AL, AR, AZ, CA, CO, DC, FL, GA, IA, ID, IL, IN, KS, KY, LA, MD, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, OH, OK, OR, PA, RI, SC, TN, TX, UT, VA, VT, WA, WI, WV, WY
9	1984	RI	CT, MA, ME
10	1985	DC	FL, MD, NC, VA
11	1985	FL	DC, GA, NC, TN, VA
12	1985	GA	FL, NC, TN, VA
13	1985	ID	NV, UT
14	1985	KY	OH, TN, VA
15	1985	MD	DC, VA
16	1985	NC	DC, FL, GA, TN, VA
17	1985	NV	ID, UT
18	1985	OH	KY
19	1985	TN	FL, GA, KY, NC, VA
20	1985	UT	ID, NV
21	1985	VA	DC, FL, GA, KY, MD, NC, TN
22	1986	AZ	All
23	1986	DC	AL, AR, AZ, CA, CO, CT, GA, IA, ID, IL, IN, KS, KY, LA, MA, ME, MI, MN, MO, MS, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, SC, TN, TX, UT, VT, WA, WI, WV, WY
24	1986	FL	SC

continued on next page

[6] Utah's national nonreciprocal law effective on Dec 31, 1987 is considered effective in 1988.

Table A.1 – *Continued from previous page*

NO	YEAR	HOME	FOREIGN
25	1986	GA	KY, SC
26	1986	ID	OR
27	1986	IL	IN, KY, MI, MO
28	1986	IN	IL, KY, MI, OH
29	1986	KY	AZ, DC, GA, IL, IN, ME, MO, NC, NJ, NY, PA, SC
30	1986	MI	IL, IN, OH
31	1986	MO	IL, KY, TN
32	1986	NC	KY, SC
33	1986	NJ	DC, KY, OH, PA
34	1986	NV	AZ, OR
35	1986	NY	AZ, DC, KY
36	1986	OH	DC, IN, MI, NJ, PA
37	1986	OR	AZ, CA, ID, NV, UT, WA
38	1986	PA	DC, KY, NJ, OH
39	1986	SC	DC, FL, GA, KY, NC, TN, VA
40	1986	TN	MO, SC
41	1986	UT	AZ, OR
42	1986	VA	SC
43	1987	AL	DC, FL, GA, KY, LA, MD, NC, SC, TN, VA
44	1987	CA	AZ, OR, TX, WA
45	1987	CT	NH
46	1987	FL	AL, LA, MD
47	1987	GA	AL, DC, LA, MD
48	1987	ID	WA, WY
49	1987	IL	WI
50	1987	IN	TN, WI
51	1987	KY	AL, LA, MD, OK, TX, WA, WI, WY
52	1987	LA	AL, DC, FL, GA, KY, MD, NC, OK, SC, TN, TX, VA
53	1987	MA	NH
54	1987	MD	AL, FL, GA, KY, LA, NC, PA, SC
55	1987	MI	WI
56	1987	MN	WI
57	1987	MO	OK
58	1987	NC	AL, LA, MD
59	1987	NH	CT, MA, ME, RI
60	1987	NV	WA, WY
61	1987	NY	OK, TX, WA, WY
62	1987	OH	WI
63	1987	OK	All
64	1987	PA	MD
65	1987	RI	NH
66	1987	SC	AL, LA, MD
67	1987	TN	AL, IN, LA
68	1987	TX	All
69	1987	UT	WA, WY
70	1987	VA	AL, LA
71	1987	WA	AZ, CA, DC, ID, KY, ME, NV, NY, OK, OR, TX, UT, WY
72	1987	WI	IL, IN, KY, MI, MN, OH
73	1987	WY	All
74	1988	AL	MS, TX, WV
75	1988	CA	ID, UT
76	1988	CO	AZ, OK, UT, WY

continued on next page

Table A.1 – *Continued from previous page*

NO	YEAR	HOME	FOREIGN
77	1988	CT	VT
78	1988	FL	WV
79	1988	ID	AL, AR, AZ, CA, CO, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NY, OH, OK, PA, RI, SC, TN, TX, VA, VT, WI, WV
80	1988	IN	WV
81	1988	KY	ID, MI, RI, UT, WV
82	1988	LA	MS, WV
83	1988	MA	VT
84	1988	MD	TN, WV
85	1988	MI	AZ, DC, ID, KY, ME, NJ, NY, OK, RI, TX, UT, WA, WV, WY
86	1988	MN	ID, WA, WY
87	1988	MS	AL, LA, TN
88	1988	NC	TX, WV
89	1988	NH	VT
90	1988	NJ	AZ, ID, ME, MI, NY, OK, RI, TX, UT, WA, WV, WY
91	1988	NY	ID, MI, NJ, OH, RI, UT, WV
92	1988	OH	AZ, ID, ME, NY, OK, RI, TX, UT, WA, WV, WY
93	1988	PA	WV
94	1988	RI	AZ, DC, ID, KY, MI, NJ, NY, OH, OK, TX, UT, VT, WA, WV, WY
95	1988	SC	WV
96	1988	TN	DC, MD, MS, WV
97	1988	UT	AL, AR, CA, CO, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NY, OH, OK, PA, RI, SC, TN, TX, VA, VT, WI, WV
98	1988	VA	WV
99	1988	VT	CT, MA, ME, NH, RI
100	1988	WA	MI, MN, NJ, OH, RI, WV
101	1988	WV	AL, AZ, DC, FL, ID, IN, KY, LA, MD, ME, MI, NC, NJ, NY, OH, OK, PA, RI, SC, TN, TX, UT, VA, WA, WY
102	1989	AL	AR
103	1989	AR	AL, DC, FL, LA, MD, MO, MS, NC, OK, SC, TN, TX, VA, WV
104	1989	CA	NM, NV
105	1989	CO	NM
106	1989	FL	AR
107	1989	KY	NM, NV, OR
108	1989	LA	AR, AZ, ID, ME, MI, NJ, NM, NV, NY, OH, OR, RI, UT, WA, WY
109	1989	MD	AR
110	1989	MI	LA, NM, NV, OR
111	1989	MO	AR
112	1989	MS	AR
113	1989	NC	AR
114	1989	NJ	LA, NM, NV, OR
115	1989	NM	All
116	1989	NV	AL, AR, CA, CO, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NY, OH, OK, PA, RI, SC, TN, TX, VA, VT, WI, WV
117	1989	NY	LA, NM, NV, OR
118	1989	OH	LA, NM, NV, OR
119	1989	OR	AL, AR, CO, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NY, OH, OK, PA, RI, SC, TN, TX, VA, VT, WI, WV, WY
120	1989	RI	LA, NM, NV, OR
121	1989	SC	AR
122	1989	TN	AR
123	1989	VA	AR

continued on next page

Table A.1 – *Continued from previous page*

NO	YEAR	HOME	FOREIGN
124	1989	WA	LA, NM
125	1989	WV	AR, NM, NV, OR
126	1990	CO	NE
127	1990	CT	AZ, DC, ID, IL, KY, LA, MI, NJ, NM, NV, NY, OH, OK, OR, PA, TX, UT, WA, WV, WY
128	1990	FL	MS
129	1990	GA	MS
130	1990	IL	AZ, CT, DC, ID, LA, MA, ME, MN, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WV, WY
131	1990	IN	MN, PA
132	1990	KY	CT, MA, MS, NH, VT
133	1990	LA	CT, IL, MA, NH, PA, VT
134	1990	MA	AZ, DC, ID, IL, KY, LA, MI, NJ, NM, NV, NY, OH, OK, OR, PA, TX, UT, WA, WV, WY
135	1990	MI	CT, MA, NH, PA, VT
136	1990	MN	IL, IN, NE
137	1990	MO	NE
138	1990	MS	FL, GA, KY, NC, SC, TX, VA, WV
139	1990	NC	MS
140	1990	NE	CO, MN, MO, WY
141	1990	NH	AL, AR, AZ, CA, CO, DC, FL, GA, IA, ID, IL, IN, KS, KY, LA, MD, MI, MN, MO, MS, MT, NC, ND, NE, NJ, NM, NV, NY, OH, OK, OR, PA, SC, TN, TX, UT, VA, WA, WI, WV, WY
142	1990	NJ	CT, IL, MA, NH, VT
143	1990	NY	CT, IL, MA, NH, PA, VT
144	1990	OH	CT, IL, MA, NH, VT
145	1990	PA	AZ, CT, ID, IL, IN, LA, MA, ME, MI, NH, NM, NV, NY, OK, OR, RI, TX, UT, VT, WA, WY
146	1990	RI	IL, PA
147	1990	SC	MS
148	1990	VA	MS
149	1990	VT	AZ, DC, ID, IL, KY, LA, MI, NJ, NM, NV, NY, OH, OK, OR, PA, TX, UT, WA, WV, WY
150	1990	WA	CT, IL, MA, NH, PA, VT
151	1990	WV	CT, IL, MA, MS, NH, VT
152	1991	AR	NE
153	1991	CA	CO, CT, DC, IL, KY, LA, MA, ME, MI, ND, NE, NH, NJ, NY, OH, OK, PA, RI, TN, VT, WV, WY
154	1991	CO	AL, AR, CA, CT, DC, FL, GA, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NH, NJ, NV, NY, OH, OR, PA, RI, SC, TN, TX, VA, VT, WA, WI, WV
155	1991	CT	CA, CO, ND, NE, TN
156	1991	IA	IL, MN, MO, NE, WI
157	1991	IL	CA, CO, IA, ND, NE, TN
158	1991	KY	CA, CO, ND, NE
159	1991	LA	CA, CO, ND, NE
160	1991	MA	CA, CO, ND, NE, TN
161	1991	MI	CA, CO, ND, NE, TN
162	1991	MN	CO, IA, ND
163	1991	MO	IA
164	1991	ND	AZ, CA, CO, CT, DC, ID, IL, KY, LA, MA, ME, MI, MN, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TN, TX, UT, VT, WA, WV, WY
165	1991	NE	AR, AZ, CA, CT, DC, IA, ID, IL, KY, LA, MA, ME, MI, ND, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TN, TX, UT, VT, WA, WV
166	1991	NJ	CA, CO, ND, NE, TN
167	1991	NY	CA, CO, ND, NE, TN
168	1991	OH	CA, CO, ND, NE, TN
169	1991	PA	CA, CO, ND, NE, TN
170	1991	RI	CA, CO, ND, NE, TN

continued on next page

Table A.1 – *Continued from previous page*

NO	YEAR	HOME	FOREIGN
171	1991	TN	AZ, CA, CO, CT, ID, IL, MA, ME, MI, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WY
172	1991	VT	CA, CO, ND, NE, TN
173	1991	WA	CO, ND, NE, TN
174	1991	WI	IA
175	1991	WV	CA, CO, ND, NE
176	1992	AR	KS
177	1992	CA	IN
178	1992	CT	IN
179	1992	IN	AZ, CA, CO, CT, DC, ID, LA, MA, ME, ND, NE, NH, NJ, NM, NV, NY, OK, OR, RI, TX, UT, VT, WA, WY
180	1992	KS	AR, CO, MO, NE, OK
181	1992	LA	IN
182	1992	MA	IN
183	1992	MI	MN
184	1992	MN	MI, OH
185	1992	MO	KS
186	1992	ND	IN
187	1992	NE	IN, KS
188	1992	NJ	IN
189	1992	NY	IN
190	1992	OH	MN
191	1992	RI	IN
192	1992	VT	IN
193	1992	WA	IN
194	1993	MN	MT
195	1993	MT	CO, ID, MN, ND, WY
196	1993	ND	MT
197	1994	CA	MN, NC, VA
198	1994	CT	MN, NC, VA
199	1994	IL	NC, VA
200	1994	IN	NC, VA
201	1994	KY	MN
202	1994	LA	MN
203	1994	MA	MN, NC, VA
204	1994	MI	NC, VA
205	1994	MN	AZ, CA, CT, DC, KY, LA, MA, ME, NC, NH, NJ, NM, NV, NY, OK, OR, PA, RI, TN, TX, UT, VA, VT, WV
206	1994	NC	AZ, CA, CO, CT, ID, IL, IN, MA, ME, MI, MN, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, UT, VT, WA, WY
207	1994	ND	NC, VA
208	1994	NE	NC, VA
209	1994	NJ	MN, NC, VA
210	1994	NY	MN, NC, VA
211	1994	OH	NC, VA
212	1994	PA	MN, NC, VA
213	1994	RI	MN, NC, VA
214	1994	TN	MN
215	1994	VA	AZ, CA, CO, CT, ID, IL, IN, MA, ME, MI, MN, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WY
216	1994	VT	MN, NC, VA
217	1994	WA	NC, VA

continued on next page

Table A.1 – *Continued from previous page*

NO	YEAR	HOME	FOREIGN
218	1994	WV	MN
219	1995	AL	AZ, CA, CO, CT, IA, ID, IL, IN, KS, MA, ME, MI, MN, MO, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, UT, VT, WA, WI, WY
220	1995	AR	AZ, CA, CO, CT, GA, IA, ID, IL, IN, KY, MA, ME, MI, MN, MT, ND, NH, NJ, NM, NV, NY, OH, OR, PA, RI, UT, VT, WA, WI, WY
221	1995	CA	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
222	1995	CT	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
223	1995	FL	AZ, CA, CO, CT, IA, ID, IL, IN, KS, KY, MA, ME, MI, MN, MO, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WI, WY
224	1995	GA	AR, AZ, CA, CO, CT, IA, ID, IL, IN, KS, MA, ME, MI, MN, MO, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WI, WV, WY
225	1995	IA	AL, AR, AZ, CA, CO, CT, DC, FL, GA, ID, IN, KS, KY, LA, MA, MD, ME, MI, MS, MT, NC, ND, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, SC, TN, TX, UT, VA, VT, WA, WV, WY
226	1995	IL	AL, AR, FL, GA, KS, MD, MS, MT, SC
227	1995	IN	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC
228	1995	KS	AL, AZ, CA, CT, DC, FL, GA, IA, ID, IL, IN, KY, LA, MA, MD, ME, MI, MN, MS, MT, NC, ND, NH, NJ, NM, NV, NY, OH, OR, PA, RI, SC, TN, TX, UT, VA, VT, WA, WI, WV, WY
229	1995	KY	AR, FL, IA, KS, MT
230	1995	LA	IA, KS, MO, MT, WI
231	1995	MA	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
232	1995	MD	AZ, CA, CO, CT, IA, ID, IL, IN, KS, MA, ME, MI, MN, MO, MS, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, RI, TX, UT, VT, WA, WI, WY
233	1995	MI	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC
234	1995	MN	AL, AR, FL, GA, KS, MD, MO, MS, SC
235	1995	MO	AL, AZ, CA, CO, CT, DC, FL, GA, ID, IN, LA, MA, MD, ME, MI, MN, MS, MT, NC, ND, NH, NJ, NM, NV, NY, OH, OR, PA, RI, SC, TX, UT, VA, VT, WA, WI, WV, WY
236	1995	MS	AZ, CA, CO, CT, DC, IA, ID, IL, IN, KS, MA, MD, ME, MI, MN, MO, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, UT, VT, WA, WI, WY
237	1995	MT	AL, AR, AZ, CA, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MO, MS, NC, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, SC, TN, TX, UT, VA, VT, WA, WI, WV
238	1995	NC	IA, KS, MO, MT, WI
239	1995	ND	AL, AR, FL, GA, IA, KS, MD, MO, MS, SC, WI
240	1995	NE	AL, FL, GA, MD, MS, MT, SC, WI
241	1995	NJ	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
242	1995	NY	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
243	1995	OH	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC
244	1995	PA	AL, AR, FL, GA, IA, KS, MO, MS, MT, SC, WI
245	1995	RI	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
246	1995	SC	AZ, CA, CO, CT, IA, ID, IL, IN, KS, MA, ME, MI, MN, MO, MT, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, TX, UT, VT, WA, WI, WY
247	1995	TN	IA, KS, MT, WI
248	1995	VA	IA, KS, MO, MT, WI
249	1995	VT	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
250	1995	WA	AL, AR, FL, GA, IA, KS, MD, MO, MS, MT, SC, WI
251	1995	WI	AL, AR, AZ, CA, CO, CT, DC, FL, GA, ID, KS, LA, MA, MD, ME, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, NY, OK, OR, PA, RI, SC, TN, TX, UT, VA, VT, WA, WV, WY
252	1995	WV	GA, IA, KS, MO, MT, WI

B Data Appendix

B.1 Firm Establishment Data

B.1.1 Data source

Data of firm establishment location and employment come from Dun & Bradstreet (D&B). They were downloaded using the online platform, Mergent Data Explr. Individual data files by state-years were downloaded in CSV format. The platform is also able to produce annual data files in zipped CSV format. However, reading these zipped CSV files in such statistical software as R could result in incomplete loading of the dataset. The cause of this issue is unclear. I conjecture that the raw data files contain irregular characters that may be misinterpreted by the statistical software as the terminal character of the file. Therefore, a safe practice is to download raw data files in each year state by state, load the files as is into a software, and finally separate the lines by commas.

B.1.2 Ownership structure

D&B datasets contain detailed information about firm ownership structure. This information is essential for identifying boundaries of a firm and for measuring its operations across regions. Each observation in the dataset is an establishment, each assigned a unique identifier called DUNSNO. It is also associated with its headquarter ID by variable HQDUNSNO, its immediate parent ID by PARENTDUNSNO, and its ultimate parent ID by ULTDUNSNO. However, the original ownership information in the raw data may contain inconsistencies or errors, such as missing values, multiple parents, and infinite loops in ownership, etc. I follow the procedures below to construct a consistent ownership table for each year of the datasets. Since HQDUNSNO is the lowest level of a firm (or a group of establishments), it suffices to find the ultimate parents of these HQDUNSNOs.

1. **Preliminary ownership table.** To start, I construct a preliminary ownership table from the raw data file. First, assign an establishment's own id DUNSNO to its HQDUNSNO if the latter is missing, and then retain observations of HQDUNSNOs with non-missing values of either PARENTDUNSNO or ULTDUNSNO. This results in a table of triplets HQ-PARENT-ULT that contains firms with a higher level owner. HQDUNSNOs with PARENTDUNSNO and ULTDUNSNO both missing are assumed to be ultimately owned by HQDUNSNO itself, unless further modifications on the ownership structure occur in later stages.

2. **Immediate parent table.** For those HQs with non-missing PARENTDUNSNO in the

preliminary ownership table, I extract a table of immediate parents (HQ-PARENT) after fixing multiple matches. Multiple matches are corrected according to data in adjacent years. I then apply this immediate parent table repeatedly to trace out higher levels of parents for each HQ until no higher parent can be found. Infinite loops may occur in this step when, for instance, two entities appear to be parents of each other. Typically, these incidents are manually fixed by removing the parent of one of the entities in the loop. To determine which entity's parent to remove, I include data from adjacent years to decide which one tends to be of higher level.

3. **Direct ultimate parents.** For observations with non-missing ULTPARENT in the preliminary ownership table, I reframe the table into duplets of direct ultimate parents so that each ULTPARENT is associated with all its subsidiaries in original columns of HQDUNSNO or PARENTDUNSNO. I then check if any entity is associated with multiple ULTDUNSNOs. Corrections are made according to the ownership structure suggested in the immediate parent table constructed in the previous step or data in adjacent years.

4. **Consistency check.** With the tables of immediate parents and direct ultimate parents at hand, I can assign ultimate owners to HQs in the preliminary ownership table in two ways, one tracing through immediate parents and the other through direct ultimate parents. Since not all immediate parents appear in the the column PARENTDUNSNO and some ULTDUNSNOs may still have PARENTDUNSNO, tracing the ownership through either approach would require using both the immediate parent table and the direct ultimate parent table. Specifically, to implement the first approach of tracing through immediate parents, I first link each HQ in the preliminary ownership table to a candidate ultimate parent using the immediate parent table. I then apply the direct ultimate parent table once to link this candidate ultimate owner to a second candidate ultimate owner. The immediate parent table is applied again to link the second candidate ultimate owner to a third. Similarly, to implement the second approach of tracing through direct ultimate parent, I first apply the direct ultimate parent table and then the immediate parent table. Finally, I check if these two approaches produce the same ultimate owner. If not, modifications will be made to immediate parents or direct ultimate parents.

B.1.3 Multistate firms

With the ownership table at hand, I now turn to construct a dataset of multistate firms.

1. Use the ownership table to identify the ultimate owner of each establishment.

2. If the ultimate owner is a non-financial non-government entity, then we are done. If the ultimate owner is a government entity (SIC 91–97), then it is excluded from our analysis with all its subsidiary establishments. If the ultimate owner is a financial company (SIC 60–67), then I find its highest level subsidiaries that are in the real sector and consider these subsidiaries as separate firms if there is more than one.

3. Exclude establishments that are financial entities controlled by these firms. Retain firms with operations in multiple states and at least 500 employees in total.

B.2 Merged DealScan-D&B Data

This section provides descriptive statistics on the merged DealScan-D&B dataset. The dataset is constructed by matching borrowers in DealScan to Dun & Bradstreet based on information on company name, industry and locations that are available in either databases. I retain the sample of loans in DealScan that are designated to US non-financial borrowers.

Figure B.1 shows the sample size of the merged dataset. Panel A plots the number of unique non-financial US borrowers in DealScan, panel B the number of loans, and Panel C the dollar amount of loans. The grey bars represent the entire DealScan sample of loans by US non-financial firms, while the black bars represent the fraction of loans whose borrowers can be matched to Dun & Bradstreet. As the figure shows, I was able to match almost all non-financial borrowers in DealScan to Dun & Bradstreet.

Table B.1 presents summary statistics for borrowing firms in the merged dataset in terms of their total employment, number of counties or states they operate in.

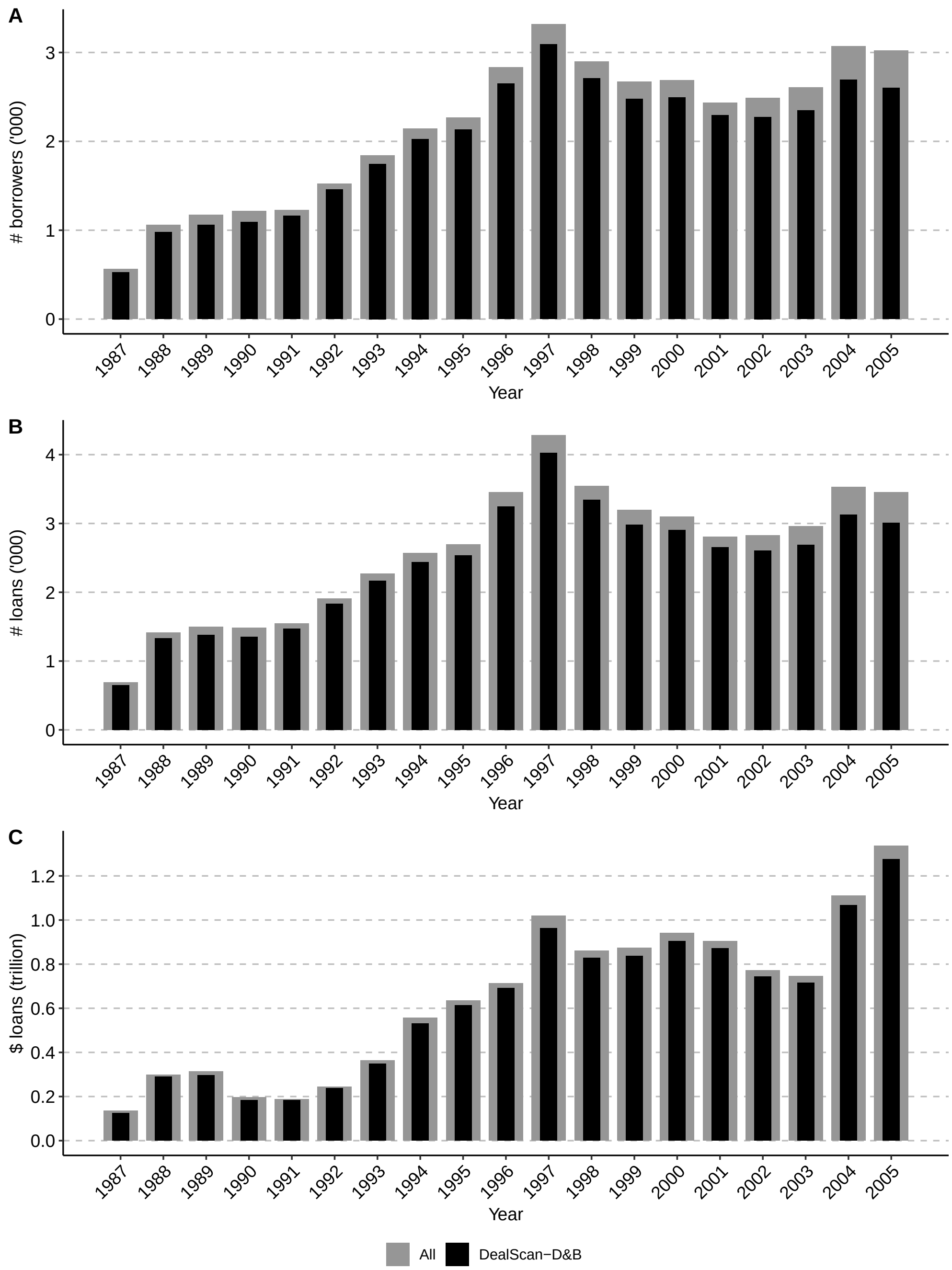

Figure B.1: Sample Size of the Merged DealScan-DunBradstreet Dataset

Notes: This figure plots the sample size of the merged DealScan-DunBradstreet dataset. Panel A plots the total number of unique US nonfinancial borrowers (in thousands) in DealScan, and the number of borrowers that can be matched to Dun & Bradstreet. Panel B plots the total number of loan packages (in thousands) in DealScan and those whose borrowers can be matched to Dun & Bradstreet. Panel C plots the total amount of loan packages (in trillions) in DealScan and those whose borrowers can be matched to Dun & Bradstreet.

Table B.1: Summary Statistics for Borrowers in Merged DealScan-D&B Dataset

Year	Variable	Observations	Mean	SD	Q25	Q50	Q75
1987	Employment	563	6347.3	17034.7	114	726	2821.4
	# Counties	563	32.2	68.1	2	7	20
	# States	563	10.1	12.5	1	4	10
1988	Employment	1058	5654.5	15370.9	117.8	716	2345.9
	# Counties	1058	29.3	59.1	2	7	19
	# States	1058	9.5	11.4	1	4	10
1989	Employment	1171	4586.5	12712.6	115	625	2142
	# Counties	1171	32.1	75.3	2	6	18
	# States	1171	9.4	11.7	1	4	10
1990	Employment	1214	5016.9	15137.9	108.5	623.5	2145.1
	# Counties	1214	29.1	62.5	2	6	17
	# States	1214	9	11.4	1	4	9
1991	Employment	1228	4937.1	15631.7	170.8	880	2553.3
	# Counties	1228	32.5	75.2	2	8	23
	# States	1228	9.6	11.4	2	4.5	11
1992	Employment	1525	5659.4	17006.2	203	1070	2931.2
	# Counties	1525	38.8	89.9	3	10	25
	# States	1525	10.6	12.1	2	5	12
1993	Employment	1842	6237.8	23562.3	198.2	929.5	2837.2
	# Counties	1842	36.6	79.5	2	9	26
	# States	1842	10.5	12.1	2	5	12
1994	Employment	2145	6881.9	23290.9	212	1000	2983.4
	# Counties	2145	43.1	98.2	3	10	26
	# States	2145	11.1	12.7	2	5	12
1995	Employment	2270	5893.2	21094.9	200	1008.5	2852.3
	# Counties	2270	41.6	98.3	3	9	26
	# States	2270	10.8	12.5	2	5	12
1996	Employment	2833	5201	19418	153	735	2187.4
	# Counties	2833	39.4	100.9	2	8	23
	# States	2833	10.2	12.2	2	5	11
1997	Employment	3320	5009.7	18448.5	152	703	2154.3
	# Counties	3320	37.7	96.9	2	8	20
	# States	3320	10	11.9	2	5	11
1998	Employment	2898	5069.1	20845.2	142.2	666.5	2018.7
	# Counties	2898	37.4	92.6	2	8	21
	# States	2898	10	11.8	2	5	11
1999	Employment	2673	6368.7	24829.7	168	804	2555.4
	# Counties	2673	45.2	110.1	2	9	26
	# States	2673	11.1	12.8	2	5	13
2000	Employment	2687	7257.9	24936.5	174	970	3195.8
	# Counties	2687	51	118.4	2	10	29
	# States	2687	11.8	13.4	2	6	14
2001	Employment	2436	8687.4	29332.9	200	1151.5	3806
	# Counties	2436	61	138.7	3	11	35
	# States	2436	12.8	14.2	2	6	15
2002	Employment	2487	7419.3	25414.7	211	1221	3588.2
	# Counties	2487	59.1	133.7	3	12	38
	# States	2487	12.9	14	2	7	16
2003	Employment	2609	6442.4	22316.9	175	1038	3193.4
	# Counties	2609	57.5	129.9	2	11	31
	# States	2609	12.4	13.9	2	6	15
2004	Employment	3069	5710.1	23895.5	125	916	2687.2
	# Counties	3069	54.2	132.1	2	10	30
	# States	3069	11.8	13.6	1	6	14
2005	Employment	3021	5937.4	26688	76	772	2522
	# Counties	3021	50.5	126.7	1	9	28
	# States	3021	11.2	13.3	1	5	13

Notes: This table reports summary statistics of the borrowers in the merged DealScan-D&B dataset. These include the total employment, the number of counties and states of operation.

C Additional Results

Table C.1 presents coefficient estimates from Equation 4 for entry outcomes in one to ten years since deregulation.

Table C.2 reports heterogeneous effects on entry outcomes in one to ten years since deregulation.

Table C.1: Multistate Firms and Bank Entry: Results for all years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Entry_{+1}	Entry_{+2}	Entry_{+3}	Entry_{+4}	Entry_{+5}	Entry_{+6}	Entry_{+7}	Entry_{+8}	Entry_{+9}	Entry_{+10}
Old Neighbours	0.592^{***}	0.926^{***}	1.180^{***}	1.44^{***}	1.57^{***}	1.84^{***}	2.01^{***}	2.01^{***}	2.26^{***}	2.72^{***}
	(0.157)	(0.266)	(0.296)	(0.351)	(0.397)	(0.430)	(0.460)	(0.465)	(0.527)	(0.668)
LogDist	-0.567^{***}	-0.748^{***}	-0.816^{***}	-1.02^{***}	-1.16^{***}	-1.38^{***}	-1.59^{***}	-1.69^{***}	-1.86^{***}	-2.02^{***}
	(0.159)	(0.168)	(0.171)	(0.195)	(0.216)	(0.269)	(0.288)	(0.290)	(0.314)	(0.329)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Var (%)	0.11	0.19	0.23	0.28	0.35	0.42	0.52	0.57	0.63	0.75
R^2 Adj	0.124	0.146	0.158	0.159	0.160	0.172	0.192	0.200	0.207	0.242
Observations	673,006	653,257	632,528	598,524	566,286	536,010	513,353	488,366	467,785	442,097

Notes: This table reports regression results of the linear probability model of bank entry in Equation 4. The dependent variable $Entry_{+h}$ is an indicator for whether bank controls a branch in the destination county, h years after deregulation. Variable *Old Neighbours* measures employment share in the destination county of a bank's original neighbouring firms, divided by 100. Variable *LogDist* measures the log geodesic distance between the bank's headquarters and the destination county (in miles), divided by 100. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.

Table C.2: Mutistate Firms and Bank Entry: Heterogeneous Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Entry_{+1}	Entry_{+2}	Entry_{+3}	Entry_{+4}	Entry_{+5}	Entry_{+6}	Entry_{+7}	Entry_{+8}	Entry_{+9}	Entry_{+10}
Old N'bours	0.0726	0.00326	0.177	0.283	0.532	0.518	0.167	−0.343	−0.50	−1.06
	(0.185)	(0.298)	(0.353)	(0.430)	(0.495)	(0.590)	(0.654)	(0.628)	(0.733)	(0.883)
Old N'bours × C&I Loan	3.4000^{***}	6.05000^{**}	6.580^{**}	7.550^{**}	6.810^{**}	8.670^{**}	12.000^{***}	15.500^{***}	18.20^{***}	25.10^{***}
	(1.270)	(2.590)	(2.890)	(3.130)	(2.990)	(3.570)	(4.300)	(4.890)	(6.090)	(8.620)
LogDist	-0.5680^{***}	-0.75000^{***}	-0.817^{***}	-1.020^{***}	-1.160^{***}	-1.390^{***}	-1.590^{***}	-1.690^{***}	-1.87^{***}	-2.03^{***}
	(0.160)	(0.168)	(0.171)	(0.196)	(0.217)	(0.269)	(0.288)	(0.290)	(0.314)	(0.329)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Var (%)	0.11	0.19	0.23	0.28	0.35	0.42	0.52	0.57	0.63	0.75
R^2 Adj	0.124	0.146	0.158	0.159	0.16	0.172	0.192	0.20	0.207	0.242
Observations	672,990	653,241	632,512	598,508	566,270	535,994	513,337	488,366	467,785	442,097

Notes: This table reports regression results from Equation 4, allowing heterogenous effects across bank characteristics. The dependent variable $Entry_{+h}$ is an indicator for whether bank controls a branch in the destination county, h years after deregulation. Variable *Old Neighbours* is the employment share in the destination county by the bank's original neighbouring firms. Variable *C&I Loan* is the share of commercial and industrial loans out of bank's total assets. Standard errors are clustered at bank and county levels. Significance levels: ***1%, **5%, *10%.