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Diversification of geographic risk in retail bank networks: evidence from bank expansion after the Riegle-Neal Act

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The 1994 Riegle-Neal Act (RN) removed restrictions on branch-network expansion for banks in the United States. An important motivation was to facilitate geographic risk diversification (GRD). Using a factor model to measure banks' geographic risk, we show that RN expanded GRD possibilities in small states, but only some large banks took advantage. Using our measure of geographic risk and an empirical model of branch-network choice, we identify preferences toward GRD separately from other factors possibly limiting network expansion. Counterfactuals show that risk negatively affected bank value but was counterbalanced by economies of density/scale, reallocation/merging costs, and local market power concerns.

1. Introduction

■ Despite the rise of the Internet, branching is still the most important tool that banks have to capture deposits.[1] To increase its share of deposits, a bank should expand its branch network. As in other retail networks, economies of scale, economies of density, and reallocation costs play important roles in the size, spatial configuration, and evolution of branch networks. For retail banking, an additional factor that is often mentioned as important in determining the optimal configuration of branch networks is *geographic risk diversification* (GRD). Branches attract deposits

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[1] According to the 2007 annual survey of the American Bankers Association (ABA), most consumers still consider visiting physical branches to be their favorite channel for accessing banking services.

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and loans from local customers, which have significant idiosyncratic risk. In a geographically nondiversified banking system, negative local shocks can have severe consequences on bank liquidity levels and may even lead to bank failures (Calomiris, 2000). By opening branches in multiple local markets with idiosyncratic risks that are not perfectly correlated, a bank can reduce the deposit and credit risk associated with its branch portfolio. Risk can be spatially correlated, and so GRD may require banks to have branches in multiple counties, or states, or possibly even multiple countries.

In this article, we study the role of diversification of geographic deposit risk in the branch location decisions of US retail banks between 1994 and 2006. Historically, the US banking industry has been much more fragmented than elsewhere, composed of many small, locally concentrated banks. A key factor in explaining this market structure is the history of stringent restrictions on banks' ability to expand geographically, within and across states.[2] Following the large number of failures of small community banks and thrifts during the 1970s and 1980s, there was a move toward the elimination of restrictions on geographic expansion for banks. This trend culminated in 1994 with the passage of the *Riegle-Neal Interstate Banking and Branching Efficiency Act* (RN), which removed the final barriers to interstate banking and laid the foundation for the removal of restrictions on interstate branching. The result has been a substantial consolidation of the US banking industry, creating a set of large institutions that are considered too big to fail. Although there are still thousands of small and locally concentrated banks, the fraction of deposits held by the 10 largest banks tripled between 1994 and 2006, going from 12% to 36%.

Advocates of bank expansion pushed for this type of deregulation using GRD as one of their main arguments, claiming that it would provide a more stable banking system. It was believed that removing restrictions on interstate geographic expansion would be beneficial, because it would allow banks to decrease the likelihood of failure by diversifying their risk over different geographic locations. As mentioned in the Economic Report of the President in 1991: "*To the extent that interstate branching restrictions still prevent banks and thrifts from diversifying efficiently, they are obstacles to the efficiency, profitability, safety, and soundness of the financial sector. Accordingly, the Administration will propose legislation to allow interstate banking and branching*."[3]

The purpose of this article is to test the validity of the claims that RN would and did improve banks' diversification of geographic risk. Specifically, we propose an approach to measure banks' geographic risk and use this measure to present new empirical evidence on the possibilities for GRD available to banks, on the effects that RN had on these possibilities, and, most importantly, on the extent to which banks took advantage of these opportunities for diversification before and after RN.

We find that RN has expanded substantially the possibilities of geographic diversification of deposit risk for banks with headquarters in small and homogeneous states. However, few banks have taken advantage of these new possibilities. For most banks, only a very small amount of the reduction in geographic risk during this period can be attributed to out-of-state bank expansion. In contrast, we find that most of the reduction in banks' geographic risk came from within-state bank mergers. To explain these findings, we use our measure of risk to identify bank preferences toward geographic risk separately from the costs of geographic expansion of branch networks,

[2] There have been different explanations for these restrictions on expansion: from the argument that banks do not internalize the social costs of a bank failure such that, under free entry, there is excess entry relative to the social optimum (Alhadeff, 1962), to political economy interpretations (Economides, Hubbard, and Palia, 1996; Kroszner and Strahan, 1999).

[3] Chapter 5 of the Annual Report of the Council of Economic Advisors in the Economic Report of the President in 1991. Similarly, Laurence Meyer, Federal Governor from 1996 to 2002, in a speech in 1996, stated: "*The Riegle-Neal Act of 1994 essentially expands the existing regional compacts to the nation as a whole. [. . .] The removal of these artificial barriers to trade is beneficial and will likely improve efficiency and diversification of risks in the banking industry*." (www.federalreserve.gov/boarddocs/speeches/1996/19961121.htm)

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such as economies of scale and density, local market power, and merging costs. Our estimates of bank preferences are based on a structural model of banks' choice of branch networks that combines modern portfolio theory with oligopoly competition.

A fairly significant literature has developed to study the effect of geographic expansion on the level of risk faced by banks.[4] From the point of view of the empirical questions that we analyze in this article, an important limitation of these studies is the use of imprecise and generic measures of geographic diversification and risk.[5] Measures of risk such as the standard deviation of net income to assets, or the standard deviation of monthly stock returns, are not limited to the risk that can be influenced by geographic diversification. As pointed out by some authors (see Hughes et al., 1996, or Carlson, 2004), these measures of risk might hide changes in geographic risk because the ability to diversify geographically may encourage banks to take riskier positions in other parts of their business so that overall, the total risk they face is unchanged or even increases.

A key building block in our empirical approach is to obtain a measure of bank geographic risk that does not have the problems alluded to above, because it is constructed to represent strictly the risk inherent in the different geographic locations. Our empirical analysis concentrates on banks' *deposit risk*. The unexpected variability over time in a bank's total volume of deposits is a good measure of this form of risk. Total bank deposits are the sum of the deposits over all the branches, which can be located in different local markets (i.e., counties). Although some factors influencing deposit risk are systematic and therefore common across local markets, others are not. There is an unsystematic/idiosyncratic component to deposit risk that is specific to the geographic region. The existence of this idiosyncratic component makes geographic diversification potentially beneficial. Following the standard approach in empirical finance (Ross, 1976; Fama and French, 1992, 1993), we use a factor model to have a parsimonious specification for the variance-covariance matrix of deposit risks at each of the 3100 US counties. We estimate this factor model using panel data on deposits at the county level. For most counties, the estimated level of deposit risk is quite substantial. The 10th and 90th percentiles in the county-level distribution of systematic risk are 0.6 and 2.3 percentage points, and the same percentiles in the distribution of diversifiable risk are 1.1 and 3.1 percentage points.[6] This is the level of risk that a bank would have if it operates only in one county. Given our factor-model estimates, we construct measures of expected deposits and deposit risk for the branch networks of each bank during the period 1995–2006, as well as *efficient portfolio frontiers* for each state in 1994 (pre-RN) and in 2006 (post-RN).[7]

Using our measure of risk, data on bank mergers, and a *revealed preference* approach, we identify bank preferences toward geographic risk separately from the contribution of the costs of geographic expansion. This approach is in the spirit of Jia (2008), Holmes (2011),

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[4] There have also been a number of articles that have looked at the effect of liberalization of interstate banking, and intra- and interstate branching restrictions on different economic outcomes. We discuss these literatures in Section 2 of the article.

[5] The typical study in this literature involves regressing some measure of risk on some measure of geographic diversification. Risk is measured using some balance sheet or capital market measure such as the standard deviation of net income to assets (Liang and Rhoades, 1991) or the standard deviation of monthly stock returns (Deng and Elyasiani, 2008). Geographic diversification is usually measured as a binary variable indicating whether a bank is geographically diversified (Demsetz and Strahan, 1997; Akhigbe and Whyte, 2003; Dick, 2006; Schmid and Walter, 2008), or the number of branches (White, 1984; Hughes et al., 1996; Carlson, 2004), or a deposit dispersion index (Liang and Rhoades, 1991; Deng and Elyasiani, 2008). In the case of mergers, diversification is measured by how much overlap there is between the target and the acquirer's networks (Brewer, Jackson, and Jagtiani, 2000; Emmons, Gilbert, and Yeager, 2002). The work of Levonian (1994) and Rose (1995) is closer to our approach. They obtain correlations in the rates of return of banks in different states to see whether there are possibilities for diversification from locating in multiple states.

[6] To get an idea of the magnitude of this level of risk, note that a one percentage point reduction in liquidity risk implies more than one percentage point increase in a bank rate of return on equity (ROE). For details, see the stylized model in the Appendix.

[7] This approach is related to Begenau, Piazzesi, and Schneider (2013) who use information from "call reports" of US Bank Holding Companies to construct bank portfolios of fixed income assets and, combined with the estimation of a factor model, obtain measures of banks' risk exposures in fixed income markets.

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and Ellickson, Houghton, and Timmins (2013), who have used moment inequalities methods to estimate structural models of market entry in the department store industry. For the banking industry, Akkus, Cookson, and Hortaçsu (2012) and Uetake and Wanatabe (2012) use a similar approach to estimate the determinants of bank mergers. These articles are part of a growing literature on empirical games of market entry in the banking industry that includes also important contributions by Ackerberg and Gowrisankaran (2006), Cohen and Mazzeo (2007, 2010), Ho and Ishii (2011), and Gowrisankaran and Krainer (2011). Our article contributes to this literature by incorporating GRD as a relevant determinant for the geographic structure of a retail network and identifies this determinant separately from other factors. A bank's decision of where to operate branches has similarities with a portfolio choice between risky assets, where the risky assets are the many different geographic local markets. Banks are concerned with expected profits and the aggregate geographic risk of their branch networks. Counterfactual experiments based on the estimated structural model reveal that the gains from additional geographic diversification are negligible for large banks but are an important determinant of network expansion for banks with medium and small size. However, for small banks, any concern for risk diversification is counterbalanced by economies of density and the costs of expansion. The smallest banks benefit most from geographic diversification, but these are the banks for which it is also the most costly to expand.

Our results help to explain the rash of bank failures that have occurred since the beginning of the financial crisis. Many of the failures were single-state or single-county banks that were overly exposed to local risk without being geographically diversified. Our estimation results point out reasons why banks may not have taken advantage of the opportunities for diversification afforded them by RN.

The rest of the article is structured as follows. In the next section, we provide a descriptive account of the US banking industry and its regulatory environment before and after RN. In Section 3, we present the data used in our analysis along with descriptive evidence on the evolution of the US banking industry. In Section 4, we estimate a factor model and obtain our measure of geographic risk. We then use this model in Section 5 to provide empirical evidence on the possibilities for diversification and the extent to which banks take advantage of them before and after RN. To explain these results, in Section 6, we estimate a structural model of competition between branch networks in which banks are concerned with geographic risk. Section 7 summarizes and concludes.

2. The US banking industry before and after Riegle-Neal

□ **The regulatory environment before Riegle-Neal.** The United States has a long history of geographic restrictions related to banking (establishing bank subsidiaries) and branching (establishing bank branches).[8] Prior to RN, the Douglas Amendment of the Bank Holding Company Act of 1956 and the McFadden Act of 1927 spelled out the rules for geographic expansion. These regulations expressly forbade bank holding companies (BHCs) from acquiring out-of-state banks unless the home state of the target bank allowed acquisitions. Throughout the 1970s and 1980s, most states loosened restrictions on acquisition, such that by 1993, 13 states and the District of Columbia allowed for entry by BHCs from any other state; 21 states allowed entry by BHCs from states that reciprocated this privilege; and 14 states allowed entry by BHCs, but only from states in the same geographic region and with reciprocity. However, only a very small number of large banks took advantage of these possibilities for interstate banking: as of 1994, there were 207 BHCs with subsidiaries in multiple states. These multistate BHCs accounted for only 3.8% of all the US bank companies in 1994, but they represented 66.9% of deposits.

[8] It is important to clarify the difference between interstate branching and interstate banking. Interstate banking refers to the ability of a BHC to own and operate banks in more than one state. Interstate branching refers to the ability of a single bank to operate branches in more than one state without requiring separate capital and corporate structures for each state.

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State-specific laws also forbade within-state branching until the 1980s, when individual states began loosening restrictions. Kroszner and Strahan (1999) suggest that the trend toward liberalization was related to the emergence of new technologies in deposit taking and lending, which explains why the removal of restrictions occurred earlier in states with fewer, small, and/or financially weak banks. By 1993, however, all states allowed at least limited intrastate branching.

A long literature has studied the effect of the deregulation that occurred throughout the 1970s and 1980s on a wide variety of outcomes. Michalski and Ors (2012), for instance, study the effect of deregulation on interregional trade, and Landier, Sraer, and Thesmar (2015) look at the effect on housing-price growth across states. Goetz, Laeven, and Levine (2014) study the impact on market valuations. Similarly, a number of articles have looked at the effect of liberalization of restrictions on bank expansion on different economic outcomes such as output growth (Jayaratne and Strahan, 1996), volatility (Morgan, Rime, and Strahan, 2004), the level of entrepreneurship and small business (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Kerr and Nanda, 2009), or income distribution, discrimination, and union activity (Black and Strahan, 2001; Beck, Levine, and Levkov, 2010; Levkov, 2010).

Although most states had loosened restrictions on branching within state throughout the late 1970s and the 1980s, prior to RN, interstate branching was forbidden almost entirely. The only exceptions were in the two years before RN when eight states had started to permit interstate branching, but in most cases only reciprocally and only for state-chartered banks that were too small to take advantage of cross-border opportunities (see Rose, 1997; Johnson and Rice, 2008). There were also often additional restrictions (for instance, in Nevada, entry was permitted only into counties with less than 100,000 inhabitants).

As a result, at the time of RN, there were almost no multistate banks (banks with branches in multiple states). Specifically, only 92 banks (0.72% of all banks) had branches in multiple states (this number is bigger if weighted by deposit, 11.27%). Of these banks, 63 had a presence in just two states, and 18 in just three. Moreover, many of these cases were not related to specific state-level deregulation, but to rules permitting banks to take over failed institutions and operate them as branches.[9] There was also a leapfrogging rule, which allowed banks located sufficiently close to state borders to expand across state lines by moving their head office to a neighboring state and leaving their former location as a branch of the new office.

□ **Deregulation of interstate branching: Riegle-Neal.** Despite the fact that interstate banking was possible in at least some states through BHC acquisition of banks, policy makers felt that banks were still significantly restricted in their ability to diversify geographic risk, because they could not expand geographically through interstate branching. Geographic expansion of BHCs through bank subsidiaries is more costly and does not imply the same degree of diversification as interstate branching. BHCs have complicated structures and are more costly to operate than banks. By allowing banks to expand geographically by establishing branches instead of bank subsidiaries, RN generated a number of important advantages such as the elimination of (i) separate boards of directors; (ii) multiple regulatory reports, examinations, and audits; and (iii) duplication of management costs and capital requirements (US General Accounting Office Report, 1993). This view was summarized by then Chairman of the Federal Reserve, Alan Greenspan (1990), who, in testimony in 1990 before the Committee on Banking, Housing and Urban Affairs stated: "*The McFadden Act forces state member and national banks to deliver interstate services only through separately capitalized bank holding company subsidiaries (where permitted by state law) rather than through branches. Such a system reduces the ability of many smaller banks to diversify geographically and raises costs for all banking organizations that operate in more than one state, a curious requirement as we search for ways to make banks more competitive and profitable. The McFadden Act ought to be amended to permit interstate branching by banks.*"

[9] Federal banking agencies could arrange interstate acquisitions for failed banks with total assets totalling at least $500 million.

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RN addressed this concern by relaxing restrictions on interstate branching such that banks from all states could expand anywhere in the country by branching.[10] RN also removed all remaining restrictions on interstate banking, thereby allowing BHCs to enter any state. A number of recent articles have studied the effect of RN on outcomes. For instance, Ho and Ishii (2011) and Dick (2008) examine the effect of RN on consumer welfare, focusing on the trade-off between increased branch density and increased market power. Rice and Strahan (2010) study the impact of relaxed branching restrictions on credit supply.

In the second subsection of Section 3, after presenting our data set, we provide detailed descriptive evidence on the evolution of the industry after RN. Consistent with the facts stated above, we show that following the policy change, few banks expanded via interstate banking, whereas by comparison, there was a substantial increase in interstate branching.

3. Data and descriptive evidence

□ **Data.** We focus on the period following the passage of RN, specifically, the period from 1994 to 2006. Counties, the primary administrative divisions for most states, are chosen as our market definition. In our model, the definition of a geographic market plays two important roles. First, as in other IO models of market entry, this choice determines the set of branches that are competing with each other for consumer deposits within a geographic area. Second, it defines a geographic partition of the United States that determines the set of assets in our model of branching as a portfolio choice. For the purpose of a model of local market competition, previous empirical studies on the US banking industry have considered county as their measure of geographic market (see, e.g., Calomiris and Mason, 2003; Ashcraft, 2005; Huang, 2008; Gowrisankaran and Krainer, 2011; or Uetake and Wanatabe, 2012; among others). Following the influential approach in Bresnahan and Reiss (1990, 1991), some of these previous articles consider only small and isolated rural counties. In this article, we cannot use this selection of small markets because our portfolio choice model should include all the local markets where banks operate branches in the United States. For the same reason, we cannot use only Metropolitan Statistical Areas (MSAs) as our definition of geographic market because that would exclude a large proportion of markets and branches in the United States.

For the purpose of our model of branching as a portfolio choice, the best geographic partition of the United States is the finest one that is compatible with a precise enough estimation of expected values, variances, and covariances of the geographic assets. A partition of the United States based on states could generate serious aggregation biases because expected returns and risks are very heterogeneous across locations within the same state. Our estimates of the model in the third subsection of Section 4 show strong spatial correlation in deposits-per-branch across counties indicating that a finer partition, such as census tracts or zip codes, would be pretty much redundant. County provides a convenient partition because at the county level, we can easily combine the branching activities of the depository institutions with detailed local demographic, social, and economic information. Furthermore, the boundaries of counties have been generally static in recent years, whereas those of cities, villages, and other incorporated locations have been far more subject to changes.[11] Our data set includes information from 3100 counties in the 50 states and the District of Columbia, and it excludes 43 counties with almost no population and without any bank branch for the whole sample period.

[10] RN gave states some flexibility in the manner in which interstate branching was permitted. Specifically, states had some influence over the minimum age of the target institution, the statewide deposit cap on branch acquisition, *de novo* interstate branching, and the acquisition of single branches or portions of an institution. Although we recognize that these may lead to slight differences across states in the impact of RN, the first-order effect of the regulation was to allow consolidation of acquired banks into branches of the acquiring bank, and this change was homogeneous across states.

[11] For rare cases where boundaries of counties do alter, the changes are minor and do not involve significant shifts of population or land area. For more detailed information about the history and summary description of the counties in the United States, refer to Chapter 4 of "Geographic Areas Reference Manual" of the Census Bureau, available at www.census.gov/geo/www/garm.html.

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Our branch-level information comes from the Summary of Deposit (SOD) data provided by the Federal Deposit Insurance Corporation (FDIC). The SOD data set is collected on June 30th each year, covering all institutions insured by the FDIC, including commercial banks and saving associations. The data set includes information, at the individual branch level, on deposits, address, and bank affiliation. Based on the county identifier of each branch, we can construct a measure of the number of branches and total deposits for each bank in each county.[12]

The data set does not include branch-level information on loans, and so our focus is on the geographic risk of deposits. There are several factors that justify this approach. Volatility in the total volume of deposits is a primary source of geographic risk for banks. Branch deposits are, by far, the most important source of liquidity for any commercial bank. The interbank market is the other source, but obtaining liquidity in the interbank market is more costly than from own branches. Several studies have shown that negative shocks in the supply of local deposits can affect banks' ability to supply loans (see Kashyap and Stein, 2000; Becker, 2007). Bruche and Suarez (2010) point out that when the risk of bank failure becomes significant, banks with access to abundant retail deposit funding can remain marginally financed at the relatively cheap rates paid on insured deposits, whereas the rest have to pay high spreads on uninsured wholesale funds. They note that this advantage is despite the role of the interbank market to intermediate deposit imbalances. In contrast, branch location is not the only factor that affects the geographic risk of loans. By 1994, banks were already permitted to make loans to far-away firms/consumers, and could securitize their loans, especially those related to mortgages.[13] A bank no longer needs to have a branch in a local market to provide loans in that market. In fact, it is becoming quite common to find households who have their mortgage with a bank located thousands of miles away from where they live, whereas this is still very rare for deposit accounts. Because of these factors, risk measurements for loans based only on branch location might not capture the true extent of geographic risk. Therefore, even if we had loan data at the branch level, we could not isolate the contribution of branch-network expansion toward risk reduction without information on the geographic location of the borrowers.

The US Census Bureau provides various data products through which we obtain detailed county-level characteristics to estimate our model: (i) population counts by age, gender, and ethnic group are obtained from the Population Estimates; (ii) median household income at the county level is extracted from the State and County Data Files, whereas income per capita is provided by the Bureau of Economic Analysis (BEA); (iii) information on local business activities such as two-digit industry-level employment and number of establishments is provided by the County Business Patterns; (iv) detailed geographic information, including the area and population weighted centroid of each county, and locations of the landmarks in the United States, is obtained from the Topologically Integrated Geographic Encoding and Referencing system (TIGER) data set.[14]

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

The National Information Center records the timing of major historical events, such as renaming, merger and acquisition, and bankruptcy, of all depository institutions that ever existed in the United States. This information allows us to identify all the merger cases and the involved banks during the sample period.

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

[13] For empirical evidence on this issue, see Petersen and Rajan (2002), Brevoort and Wolken (2009), and in particular, Table 3.2 in that article.

[14] To measure the geographic distance between two counties, we use the population-weighted centroid of each county and the Haversine formula (Sinnott, 1984) to account for Earth curvature.

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TABLE 1 Descriptive Statistics

	Year				
Statistics	1994	1997	2000	2003	2006
Banks:					
Number of banks	12,976	11,164	10,098	9,238	8,749
Change in number of banks during last three years		−1812	−1066	−860	−489
Openings of new banks during last three years		402	735	391	477
Closings of banks during last three years due to mergers		2154	1761	1187	937
Closings of banks during last three years due to failures		60	40	64	29
Branches:					
Number of branches	80,795	81,553	84,909	87,183	94,123
Average number of branches per bank	6.2	7.3	8.4	9.4	10.8
Median number of branches per bank	2	2	2	3	3
% *de novo* branches of banks with HQs in other state	8.9	15.8	21.6	30.9	32.7
Branch creation accounted by mergers (%):					
Overall sample	64.8	68.7	57.5	51.0	53.5
In markets within the same state as bank HQs	60.9	49.7	43.1	33.3	32.8
In markets in different state than bank HQs	82.7	91.0	75.7	65.2	67.9

TABLE 2 Distribution of Deposits-per-Branch at County Level: Year 1994 (in millions of 1990 dollars)

%	Quantile	%	Quantile	%	Quantile
minimum	0.2	25%	15.9	90%	33.3
1%	6.5	50%	20.5	95%	39.5
5%	10.5	75%	26.0	99%	56.6
10%	12.3			maximum	200.94

TABLE 3 Trends in Securitization of Loans

Year	(1) # of Banks with Positive Securitization	(2) % of Banks with Positive Securitization	(3) % of Loans Securitized	(4) Assets Share of Banks with Securitization
2001	153	1.76%	4.16%	18.17%
2002	89	1.05%	3.17%	17.36%
2003	104	1.25%	3.32%	17.35%
2004	74	0.90%	3.81%	18.02%
2005	75	0.94%	3.31%	17.39%
2006	89	1.12%	1.79%	15.75%
2007	94	1.21%	3.35%	14.72%

□ **Descriptive evidence.** Tables 1 to 3 and Figures 1 to 4 present a description of the evolution of branch networks in the US banking industry during the period 1994–2006. We want to highlight the following stylized facts: (i) starting in the 1980s, there was a wave of bank mergers that increased substantially concentration ratios in the market of deposits; (ii) banks have responded to a growing demand for deposits by opening more branches and keeping deposits-per-branch practically constant over time; (iii) geographic expansion to other states has been concentrated in large banks that have used mergers/acquisitions for this expansion; and (iv) securitization was not a universal practice by the majority of banks and it is not the reason why small banks did not expand geographically.

(i) Consolidation and wave of mergers. There has been significant consolidation of the industry, as shown by the massive and continued reduction in the number of commercial banks. The rate of decline in the number of banks slowed down during the later years of the sample. Most of the

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FIGURE 1

NUMBER OF MERGERS AND PERCENTAGE OF WITHIN-STATE MERGERS

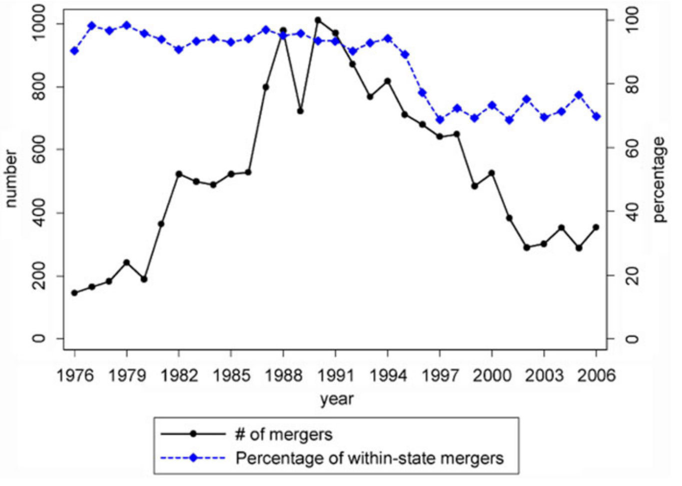
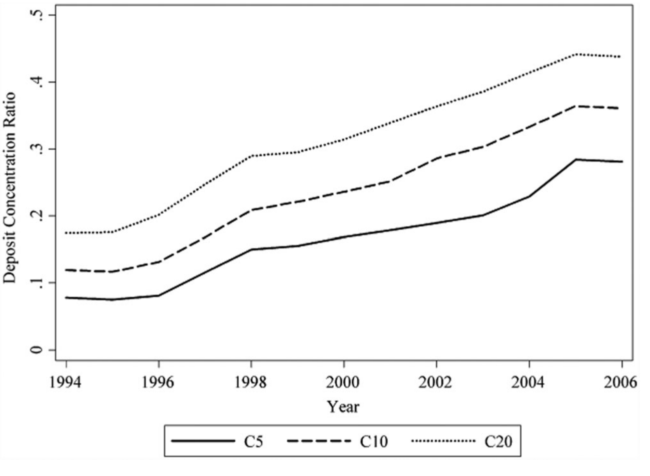


FIGURE 2

INDUSTRY CONCENTRATION RATIOS (DEPOSITS)



reduction in the number of banks has taken place through mergers and very little is explained by bank failures. Despite the significant reduction in the number of banks, there were still almost 9000 banks in 2006.[15] Figure 1 presents the time series for the annual number of bank mergers and the proportion of within-state mergers during the period 1976–2006. This figure shows that the process of consolidation started in the early 1980s with a strong wave of bank mergers that reached its peak in 1988–1992. The consequences from this merger wave can be seen in Figure 2, which plots the evolution of the 5-, 10-, and 20-firm concentration ratios, where banks are ranked according to their deposits. The figure shows that the banking industry became much more concentrated in the period following RN. Many mergers after 1994 happened among banks

[15] The number of banks has continued declining between 2006 and 2015. According to a FDIC report from December 17, 2015, the number of FDIC-insured banks was 6233. However, in contrast to our period of analysis, a significant component of the decline since 2008 is bank failures.

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FIGURE 3

CROSS-SECTIONAL DISTRIBUTIONS OF THE LOGARITHM OF DEPOSITS-PER-BRANCH

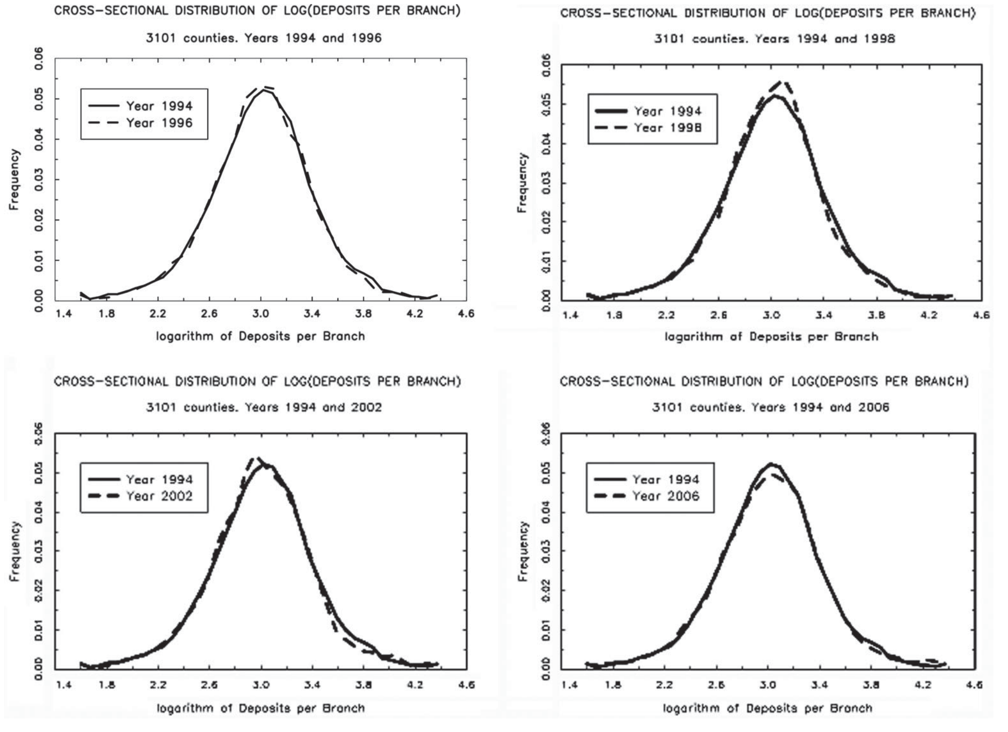
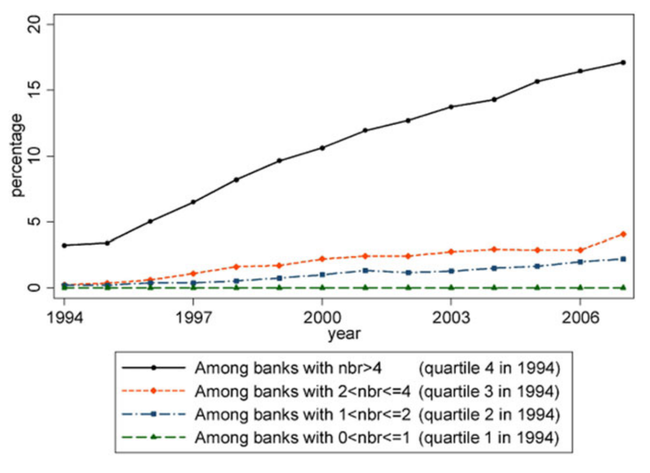


FIGURE 4

PERCENTAGE OF MULTISTATE BANKS
(by bank size as measured by number of branches)



of the same BHC. In other words, BHCs took advantage of the new regulation to convert their subsidiary banks into branches.

(ii) Growth in number of branches. Table 1 shows that, despite the decline in the number of banks, the number of branches has experienced continuous growth over our sample period, from 80,795 branches in 1994 to 94,123 in 2006. The average number of branches per bank has

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grown from 6.3 in 1994 to 10.8 in 2006. Population and wealth growth have increased demand for commercial banking services. This, together with the existence of capacity constraints at the branch level, explains part of the rising number of branches. Another factor is that the deregulation of the industry, and in particular the enactment of RN, has eliminated barriers to entry and has encouraged competition and entry of other banks. Consistent with this hypothesis, Table 1 shows that banks with headquarters (HQs) in other state have been very active in the creation of new branches. Between 1997 and 2006, these banks account for between 21% and 33% of all *de novo* branches, despite the fact that they represent a much smaller fraction of all banks.

Table 2 presents the distribution of deposits-per-branch in 1994, in millions of 1990 dollars. The sample median is $20.2 million and more than 90% of the counties have deposits-per-branch between $10 million and $40 million. This low dispersion in the size of branches, despite the large heterogeneity in the market sizes of counties, suggests that branches face substantial diseconomies of scale when growing in size such that, to accommodate an increase in consumer supply of deposits, most of the adjustment takes place through an increase in the number of branches. Figure 3 presents the cross-sectional distribution of the logarithm of deposits-per-branch for the 3100 counties for years 1994, 1996, 1998, 2002, and 2006. This distribution has been very stable over the period 1994–2006. This time-stability in the distribution of branch size, despite total deposits in real terms increasing by 51% during this period, shows again that banks have adjusted to this increase in supply of deposits almost entirely using the extensive margin, that is, increasing the number of branches.

(iii) Growth and geographic expansion through mergers. The growth in the size of commercial banks, as measured by the number of branches per bank, has taken place through the acquisition of other banks and through *de novo* branching. Table 1 shows that between half and two thirds of *branch creation* is accounted for by mergers and acquisitions.[16] This proportion is between 66% and 91% in states other than the bank's HQs, and between 33% and 50% within the same state. Therefore, whereas most of the out-of-state expansion has occurred through mergers, the within-state expansion has been both through mergers and *de novo* branching.[17]

Figure 4 shows how the proportion of multistate banks has grown steadily during the sample period. The growth is concentrated in larger banks, as measured by number of branches (a very similar pattern appears when we measure bank size by volume of deposits). Despite this growth, the proportion of "large" banks operating in multiple states is less than 20% in 2006.

Importantly, despite the fact that RN fully deregulated interstate banking (such that BHCs could expand nationally without condition), there was little growth in this form of expansion following the passage of RN. In fact, following RN, there was a slight decrease in the number of multistate BHCs. By 2007, just 3.7% (or 62.2% by deposits) of BHCs had subsidiaries in multiple states. In contrast, and consistent with the fact that the main change from RN was the ability to branch interstate, interstate branching increased considerably. By 2007, the number of multistate banks had increased 700% to 7.06% (or to 66.69% if weighted by deposits).

[16] Here we define *branch creation* in the same way as Davis and Haltiwanger (1992) defined *job creation* and *job destruction*. Total branch creation at period t is equal to $\sum_{i=1}^{I_t}\sum_{m=1}^{M} 1\{\Delta n_{imt} > 0\}\,\Delta n_{imt}$, where $1\{.\}$ is the binary indicator function, and $\Delta n_{imt} \equiv n_{imt} - n_{imt-1}$ is the change in the number of branches between years $t-1$ and t. Branch creation accounted for by mergers and acquisitions is equal to $\sum_{i=1}^{I_t}\sum_{m=1}^{M} 1\{\Delta n_{imt}^{M} > 0\}\,\Delta n_{imt}^{M}$, where Δn_{imt}^{M} is the change due to a merger or acquisition. In the Appendix, we describe our approach to identify which part of the annual variation in the number of branches of a bank in a county is associated with a merger and which part is due to *de novo* branching.

[17] Although almost every state immediately adopted RN to allow for interstate banking through mergers, some states still have not chosen to permit interstate banking through *de novo* branching. These surviving restrictions may have had an effect on the way banks enter in other states. Twenty-four states adopted *interstate branching by merger/acquisition* between 1994 and 1996, and 25 states adopted it on the deadline of June 1 1997. Only two states, Texas and Montana, opted out by that deadline, but they subsequently adopted interstate branching by merger in 1999 and 2002, respectively. Interstate branching via *de novo* establishment had to be opted into specifically. As of 1997, only 13 states allowed *de novo*, and by 2005, 22 did.

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(iv) Securitization. Table 3 reports the trend in securitization of loans calculated from the call report data sets. In particular, securitization is defined in the call data set as the "outstanding principal balance of assets sold and securitized by the reporting bank with servicing retained or with recourse or other seller-provided credit enhancements."[18] This table reveals some interesting facts on the practice of securitization by US banks during this period. First, only a very small number of banks securitized their loans. For most of the years in our sample, the number of banks with positive levels of securitization is around 100 (column 1), which accounts for about only 1% of all banks in the sample (column 2). Less than 5% of all loans issued by commercial banks are securitized (column 3). This finding is consistent with that in Jiangli and Pritsker (2008), who study securitization at the BHC level. Second, banks engaging in securitization tend to be the very large banks. Column (4) suggests that the 1% of banks that securitize hold almost 20% of total assets in the commercial banking industry. Because the big banks are also those who extensively expand their branch networks, Gilje, Loutskina, and Strahan (2013) argue that securitization and branch networks act as complementary, rather than substitute, ways to integrate local lending markets. Therefore, we consider that during our study period, securitization is far from being a universal practice by the majority of banks, and it is definitely not the reason why small banks did not expand geographically.

4. Measuring geographic risk

□ **Basic framework.** Our objective is to develop a measure of bank geographic risk that allows us to determine the possibilities for GRD available to commercial banks, on the effects that RN had on these possibilities, and on the extent to which commercial banks took advantage of these opportunities for diversification before and after RN. A commercial bank is a firm that accepts deposits, makes loans, and provides payment services. Banks operate using branches that compete in local markets.[19] We assume that the US banking industry at some period t is configured by I_t banks and M geographic local markets (e.g., counties). We index banks by i, markets by m, and time by t.

Our approach combines modern portfolio theory with oligopoly competition. From the point of view of portfolio theory, we consider the set of available assets to consist of all the geographic markets (i.e., counties) where a bank can operate branches; the unit of an asset is a branch; and the profitability of each asset is measured using the amount of deposits-per-branch in the geographic market. To measure deposit risk, and to study empirically the relationship of this risk with a bank's branch network, we estimate the expected value of deposits-per-branch at each local market and their variances and covariances across markets using a factor model. Since the seminal studies of Ross (1976) and Fama and French (1992, 1993), factor models have been commonly used in empirical finance to estimate the variance-covariance of risky assets. From the point of view of oligopoly competition, our model takes into account that the profitability of a branch depends on the number of branches and banks operating in the local market.

There are two levels of competition between retail banks in our setup: the local market (county) level, and the national level. At the level of a local market, banks compete with each other for deposits. The equilibrium in this game determines the amount of deposit each active bank has at the local market level. At the national level, each bank chooses its branch network, that is, the number of branches at each geographic local market. The *branch network* of bank i

[18] We use the second quarter call report each year in order to be consistent with the FDIC SOD data, which is collected in June. The results using other quarters look very similar. We calculate the sum of securitization among seven loan categories: family residential loans, home equity lines, credit card receivables, auto loans, other consumer loans, commercial and industrial loans, and all other loans and all leases.

[19] Two branches compete with each other for client deposits only if they are in the same local market. The existence of transportation costs imply that consumers are willing to patronize a branch only if it is not too far away from where they live. Wang (2009) and Ho and Ishii (2011) estimate spatial models of consumer demand for retail banks. They find evidence of significant consumer disutility associated with distance traveled.

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can be described as a vector $\boldsymbol{n}_{it} \equiv \{n_{imt} : m = 1, 2, \ldots, M\}$, where n_{imt} is the number of branches that bank i has in market m at period t. The equilibrium in this game of network competition determines the number of branches that every bank has at each of the M geographic markets. Liquidity from deposits can be transferred between branches of the same bank at a very low cost. A bank's liquidity is measured by the difference between its total deposits and total loans. A bank can obtain additional liquidity in the interbank money market, but this is costly.

Given this common basic framework, it is relevant to explain here some important differences between our approaches in Sections 5 and 6 below. In Section 5, we concentrate on the trade-off between expected profitability and risk of a branch network using the amount of deposits of a branch as the key measure of profitability. The model in that section assumes that banks have mean-variance preferences over deposits-per-branch and abstracts from other factors that may affect the value of a branch network, such as economies of scale and density, the endogeneity of the amount of deposits of a branch in a local market, or value-at-risk. Although these are strong assumptions, they are useful in the sense that they allow us to apply methods from modern portfolio theory that reveal interesting patterns in the trade-off between risk and expected profitability. We relax these assumptions in Section 6, where we specify and estimate a structural model of choice of branch network that incorporates economies of density and scale, adjustment costs, value-at-risk, and endogenous determination of deposits-per-branch in local markets.

□ **Model of geographic risk.** Our measure of geographic risk is based on the estimation of a panel data regression model for the logarithm of deposits-per-branch. In this regression model, we distinguish three main components: (i) the regression function, that we interpret as the expected value of the logarithm of deposits-per-branch in a county; (ii) the part of the error term that is a deterministic function of aggregate common shocks for all the counties, that we interpret as the systematic component of geographic risk; and (iii) the part of the error term that has independent variation across counties, and that we interpret as the diversifiable component of geographic risk. This regression model can be interpreted as a factor model, and we provide this interpretation below. We postulate the following model for the logarithm of deposits-per-branch in county m at year t,

$$\ln(d_{mt}) = \left[\alpha_m^{(0)} + \mathbf{X}_{mt}\boldsymbol{\alpha}^{(1)}\right] + [\mathbf{X}_{mt}\gamma_t] + u_{mt}. \quad (1)$$

The scalar $\alpha_m^{(0)} + \mathbf{X}_{mt}\boldsymbol{\alpha}^{(1)}$ is the expected value of $\ln(d_{mt})$ conditional on $\mathbf{X}_{mt}$. $\alpha_m^{(0)}$ is a county-fixed-effect, and $\boldsymbol{\alpha}^{(1)}$ is a vector of parameters.[20] $\mathbf{X}_{mt}$ is a $1 \times K$ vector of observable variables to the researcher, and $\mathbf{X}_t \equiv (\mathbf{X}'_{1t}, \mathbf{X}'_{2t}, \ldots, \mathbf{X}'_{Mt})'$ represents the information available to banks at period t. This vector includes many observable variables at the county level, such as the lagged dependent variable, lagged number of branches, log population, log income per capita, log total employment, log number of business establishments, and employment shares of 19 two-digit industries. The terms $[\mathbf{X}_{mt}\ \gamma_t]$ and u_{mt} are unobservable to the researcher and to banks. They are the unexpected or risk components. The term γ_t is a $K \times 1$ vector of random variables (or *factors*) that are common to all the markets. The term u_{mt} is a random variable that is market specific. The random variables in γ_t and u_{mt} have mean zero, are mean independent of $\mathbf{X}_t$, and are unknown to banks when they make their investment decisions at period t. The vector of unobservable factors γ_t represents the systematic risk that affects every geographic market. These K variables are i.i.d. over time, without loss of generality they have zero mean, and the $K \times K$ variance-covariance matrix is $\boldsymbol{\Sigma}_\gamma$. The effect of these systematic risk factors may vary across markets. The effect in

[20] Our specification includes county-fixed-effects in the mean of deposits and in the variance of diversifiable risk. An important issue in the measurement of geographic risk is the distinction between risk from the point of view of banks and unobserved county heterogeneity from the point of view of the researcher. A model that is not flexible enough to account for the actual heterogeneity across counties in the level and evolution of deposits will spuriously measure as diversifiable risk something that is known *ex ante* to banks.

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market m and period t is $\mathbf{X}_{mt}\ \gamma_t$. The scalar random variable u_{mt} represents the market-specific idiosyncratic risk.

A potentially important constraint for banks' GRD is the existence of strong spatial correlation in the supply of deposits of neighboring counties. This spatial correlation may not be fully captured by the factors $\mathbf{X}_{mt}\ \gamma_t$. Therefore, we allow the unobserved idiosyncratic shocks to be spatially correlated. For any county m, we define S rings or concentric bands around the county. The first band is defined as the set of counties with centers that are fewer than 200 miles away from the center of county m, excluding the own county m. The second band is the set of counties with centers between 200 and 400 miles away from the center of county m. The third band is the set of counties with centers between 400 and 1000 miles away from the center of county m, and so on. The spatial autoregressive process of u_{mt} can be represented using expression $u_{mt} = \rho_1\ \tilde{u}_{mt}^{(1)} + \rho_2\ \tilde{u}_{mt}^{(2)} + \cdots + \rho_S\ \tilde{u}_{mt}^{(S)} + e_{mt}$, where $\tilde{u}_{mt}^{(s)}$ is the mean value of the shock u in band s around county m, $\rho_1, \rho_2, \ldots, \rho_S$ are parameters, and e_{mt} is a residual shock that is not spatially correlated. We can write this spatial autoregressive process in matrix form as:

$$\mathbf{u}_t = \rho_1[\mathbf{W}_1\ \mathbf{u}_t] + \rho_2[\mathbf{W}_2\ \mathbf{u}_t] + \cdots + \rho_S[\mathbf{W}_S\ \mathbf{u}_t] + \mathbf{e}_t, \tag{2}$$

where $\mathbf{u}_t$ is the $M \times 1$ vector $(u_{1t}, u_{2t}, \ldots, u_{Mt})'$; similarly, $\mathbf{e}_t$ is the vector $(e_{1t}, e_{2t}, \ldots, e_{Mt})'$; and $\mathbf{W}'s$ are $M \times M$ weighting matrices such that the m-th row of matrix $\mathbf{W}_s$ contains 0s for county m and for counties not in ring s around county m, and the value $1/(\#$ counties in ring s around county $m)$ for every county within the ring. We also allow for conditional heteroskedasticity in the variance of the shock e_{mt}, that is, $var(e_{mt}|\mathbf{X}_t) = \exp\{\delta_m^{(0)} + \mathbf{X}_{mt}\ \boldsymbol{\delta}^{(1)}\}$, where $\delta_m^{(0)}$ is a county-fixed-effect, and $\boldsymbol{\delta}^{(1)}$ is a vector of parameters. Given this factor model, it is straightforward to show that the vector with the log-deposits-per-branch for each county at year t has the following vector of expected values and variance-covariance matrix:

$$\begin{aligned} \boldsymbol{\mu}_t &\equiv \mathbb{E}(\ln \mathbf{d}_t|\mathbf{X}_t) = \boldsymbol{\alpha}^{(0)} + \mathbf{X}_t\ \boldsymbol{\alpha}^{(1)} \\ \boldsymbol{\Omega}_t &\equiv \mathbb{V}(\ln \mathbf{d}_t|\mathbf{X}_t) = \mathbf{X}_t\ \boldsymbol{\Sigma}_\gamma\ \mathbf{X}_t' + (I - \rho\mathbf{W})^{-1}\mathbf{D}(\boldsymbol{\delta}, \mathbf{X}_t)\ (I - (\rho\mathbf{W})')^{-1}, \end{aligned} \tag{3}$$

where $\boldsymbol{\alpha}^{(0)}$ is the vector of M county-fixed-effects $(\alpha_1^{(0)}, \alpha_2^{(0)}, \ldots, \alpha_M^{(0)})'$; $\mathbf{X}_t$ is a $M \times K$ matrix; $\rho\mathbf{W}$ is the matrix $\rho_1\mathbf{W}_1 + \rho_2\mathbf{W}_2 + \cdots + \rho_S\mathbf{W}_S$; and $\mathbf{D}(\boldsymbol{\delta}, \mathbf{X}_t)$ is a $M \times M$ diagonal matrix with elements $\exp\{\delta_m^{(0)} + \mathbf{X}_{mt}\ \boldsymbol{\delta}^{(1)}\}$.

□ **Estimation of the model of geographic risk.** Using T time-dummy variables, $td_t^{(1)}, \ldots, td_t^{(T)}$, we can write the model as:

$$\ln d_{mt} = \alpha_m^{(0)} + \sum_{j=1}^{T} \left[\mathbf{X}_{mt}\ td_t^{(j)}\right]\ \gamma_j^* + u_{mt}, \tag{4}$$

where γ_t^* is a $K \times 1$ vector of "parameters" that by construction is equal to $\boldsymbol{\alpha}^{(1)} + \gamma_t$. Equation (4) is a panel data model with fixed effects $\alpha_m^{(0)}$, vector of regressors $\mathbf{X}_{mt}\ [td_t^{(1)}, td_t^{(2)}, \ldots, td_t^{(T)}]$, vector of parameters $(\gamma_1^*, \gamma_2^*, \ldots, \gamma_T^*)$, and transitory shock u_{mt}.

(Step 1) Estimation of vectors of expected log-deposits-per-branch, $\{\boldsymbol{\mu}_t\}$. We estimate the vector of parameters in this model using a fixed-effects (within-groups) estimator. As a robustness test, we have estimated the model also using the Arellano and Bond (1991) GMM estimator and we have obtained similar results.[21] Given our estimate of the vector γ_t^*'s, we estimate the fixed effect $\alpha_m^{(0)}$ as $\hat{\alpha}_m^{(0)} = T^{-1}\sum_{t=1}^{T}(\ln d_{mt} - \sum_{j=1}^{T}[\mathbf{X}_{mt} td_t^{(j)}]\widehat{\gamma_j^*})$. Then, taking into account that $\gamma_t^* \equiv \boldsymbol{\alpha}^{(1)} + \gamma_t$

[21] In dynamic panel data models, it is well known that the fixed-effects estimator is consistent only as M and T go to infinity, but not when T is small. Because the number of periods in our panel is relatively large ($T = 13$), it is arguable that the bias of the fixed-effects estimator might not be too large. The Arellano-Bond estimator is consistent when T is small.

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and $\mathbb{E}(\gamma_t) = 0$, our estimator of the vector $\boldsymbol{\alpha}^{(1)}$ is $\widehat{\boldsymbol{\alpha}}^{(1)} = T^{-1} \sum_{t=1}^{T} \widehat{\gamma_t^*}$. In addition, given $\widehat{\boldsymbol{\alpha}}^{(0)}$ and $\widehat{\boldsymbol{\alpha}}^{(1)}$, the estimated vector of expected log-deposits-per-branch is $\widehat{\boldsymbol{\mu}}_t = \widehat{\boldsymbol{\alpha}}^{(0)} + \mathbf{X}_t\, \widehat{\boldsymbol{\alpha}}^{(1)}$.

(Step 2) Estimation of variance-covariance matrices of risks, $\{\boldsymbol{\Omega}_t\}$. The estimation of matrix $\boldsymbol{\Omega}_t$ has three different parts: (i) estimation of the $K \times K$ matrix $\boldsymbol{\Sigma}_\gamma$ that accounts for the contribution of "systematic" risk to the variance $\boldsymbol{\Omega}_t$; (ii) estimation of the vector of parameters ρ that accounts for additional spatial correlation in local market shocks; and (iii) estimation of the parameters $\boldsymbol{\delta}$ that account for heteroskedasticity in variance of diversifiable risk. *(i) Estimation of matrix* $\boldsymbol{\Sigma}_\gamma$. By definition, we have that $\boldsymbol{\Sigma}_\gamma \equiv \mathbb{E}(\gamma_t \gamma_t')$. Given our estimators $\widehat{\gamma_t^*}$ and $\widehat{\boldsymbol{\alpha}}^{(1)} = T^{-1} \sum_{t=1}^{T} \widehat{\gamma_t^*}$, we have that $T^{-1} \sum_{t=1}^{T} [\widehat{\gamma_t^*} - \widehat{\boldsymbol{\alpha}}^{(1)}]\, [\widehat{\gamma_t^*} - \widehat{\boldsymbol{\alpha}}^{(1)}]'$ is a consistent estimator of matrix $\boldsymbol{\Sigma}_\gamma$. *(ii) Estimation of parameters ρ in the spatial stochastic process of the idiosyncratic shock.* Let $\widehat{u}_{mt}$ be the residual for u_{mt} from the regression in Step 1, that is, $\widehat{u}_{mt} = \ln d_{mt} - \widehat{\alpha}_m^{(0)} - \sum_{j=1}^{T} [\mathbf{X}_{mt}\; td_t^{(j)}] \widehat{\gamma_j^*}$. Given these residuals, we construct the values $\widetilde{\widetilde{u}}_{mt}^{(1)}, \widetilde{\widetilde{u}}_{mt}^{(2)}, \ldots, \widetilde{\widetilde{u}}_{mt}^{(S)}$ for the S bands in the spatial autoregressive process of u_{mt}. Then, we run an ordinary least squares (OLS) regression of $\widehat{u}_{mt}$ on $\widetilde{\widetilde{u}}_{mt}^{(1)}, \widetilde{\widetilde{u}}_{mt}^{(2)}, \ldots, \widetilde{\widetilde{u}}_{mt}^{(S)}$ to obtain consistent estimates of the parameters ρ_1, ρ_2, and ρ_S. *(iii) Estimation of parameters in the variance of diversifiable risk.* Let $\widehat{e}_{mt}$ be the OLS residuals from the estimation of the spatial process, that is, $\widehat{e}_{mt} = \widehat{u}_{mt} - \widehat{\rho}_1\, \widetilde{\widetilde{u}}_{mt}^{(1)} - \cdots - \widehat{\rho}_S\, \widetilde{\widetilde{u}}_{mt}^{(S)}$. We run an OLS regression for $\ln(|\widehat{e}_{mt}|)$ on $\mathbf{X}_{mt}$ and county-fixed effects (fixed-effects regression). This regression gives us consistent estimates of the parameters $\delta_m^{(0)}$ and $\boldsymbol{\delta}^{(1)}$. Combining steps (i), (ii), and (iii), we construct the following estimator of matrix $\boldsymbol{\Omega}_{mt}$:

$$\widehat{\boldsymbol{\Omega}_{mt}} = \mathbf{X}_{mt} \left(\frac{1}{T} \sum_{t=1}^{T} [\widehat{\gamma_t^*} - \widehat{\boldsymbol{\alpha}}^{(1)}][\widehat{\gamma_t^*} - \widehat{\boldsymbol{\alpha}}^{(1)}]' \right) \mathbf{X}_{mt}' + (I - \widehat{\rho}\mathbf{W})^{-1}\, \mathbf{D}(\widehat{\boldsymbol{\delta}}, \mathbf{X}_t)\, (I - (\widehat{\rho}\mathbf{W})')^{-1}. \quad (5)$$

Table 4 presents our estimates of the regression model of geographic risk. The number of observations in the estimation is 37, 200 (3100 counties times 12 years). The vector of market characteristics $\mathbf{X}_{mt}$ includes the 25 variables at the county level. The goodness-of-fit of the model is excellent: the R^2 coefficient for the within-groups regression is 0.54, and the equation in levels (including fixed effects) has an R^2 of 0.98.

Panel A includes estimates of parameters $\boldsymbol{\alpha}^{(1)}$ in expected log-deposits-per-branch. There is substantial persistence in the dependent variable even after controlling for county fixed effects: the parameter estimate for the lagged dependent variable is 0.7382 (SE = .0067). The logarithm of deposits-per-branch increases significantly with county population and income per capita. The employment shares of industries such as Retail Trade, Real Estate, Management, and Information Technology have a significant positive effect on log-deposits-per-branch. The distribution of county fixed effects (not reported) shows significant heterogeneity in expected log-deposits-per-branch across counties that is not explained by observable variables, for example, the interquartile difference of the fixed effects is 16%, and the difference between the 5th and 95th quantiles is 49%.

Panels B and C present summary statistics on the estimation of the structure of the unobservables in the regression model, and more specifically on the different components of risk. Panel B deals with systematic risk, as measured by $\sqrt{\mathbf{X}_{mt}\; \boldsymbol{\Sigma}_\gamma\; \mathbf{X}_{mt}'}$. We report measures of systematic risk averaged over all of the counties for the year 1995. The amount of systematic risk is substantial. Most of this risk is accounted for by the factor associated with log income (47%). The factors related to the employment shares of two-digit industries (14%) also represent important contributions to systematic risk.[22] Panel C presents estimates of the parameters in the spatial autoregressive process of residuals. We consider four bands around the geographic centroid of a county: 200 miles, 200 to 400 miles, 400 to 1000 miles, and more than 1000 miles. There is strong spatial correlation in the residuals, that declines with distance and becomes insignificant for distances greater than 1000 miles. In the estimation of the parameters $\delta_m^{(0)}$ and $\boldsymbol{\delta}^{(1)}$ in the

[22] The decomposition of the contribution of different factors does not sum to 100% because of nonzero covariances.

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TABLE 4 Regression Model for Log-Deposits-per-Branch

Panel A: Estimation of Parameters $\boldsymbol{\alpha}^{(1)}$

Variable	Estimate (SE)	Variable	Estimate (SE)
Lagged log deposits	0.7382 (0.0067)***	log Income	0.0734 (0.0140)***
Lagged log # branches	0.0343 (0.0071)***	log Total Employment	0.0411 (0.0636)
log Population	0.0990 (0.0141)***	log Total Establishments	0.0207 (0.0041)
Employment share Mining	− 0.0736 (0.0599)	Employment share Scientific	− 0.0101 (0.0807)
Employment share Utilities	0.0394 (0.0431)	Employment share Management	0.1875 (0.0471)***
Employment share Construction	− 0.0474 (0.0537)	Employment share Administrative	− 0.0103 (0.0527)
Employment share Manufacturing	0.0535 (0.0449)	Employment share Education	0.0747 (0.0455)
Employment share Wholesale	0.0721 (0.0409)	Employment share Health	0.0894 (0.0475)
Employment share Retail	0.1014 (0.0462)**	Employment share Entertainment	0.0861 (0.0415)
Employment share Transportation	0.0243 (0.0436)	Employment share Hotels	0.0688 (0.0489)
Employment share Information	0.1332 (0.0447)***	Employment share Other services	0.0684 (0.0417)
Employment share Finance	−0.0145 (0.0585)	Employment share Public Adm.	0.0045 (0.0555)
Employment share Real estate	0.1642 (0.0509)***		
County fixed effects		Yes	
Year dummies interacted with all regressors		Yes	
R^2 in levels (within county)		0.9872 (0.5420)	
Number of observations		37,200	

Panel B: Systematic Risk: $\sqrt{\mathbf{X}_{mt}\boldsymbol{\Sigma}_{\gamma}\mathbf{X}'_{mt}}$. Year 1995 (mean over counties)

Variable	Risk (% of Total)	Variable	Risk (% of Total)
Total	0.5829 (100%)	Lagged log deposits	0.0499 (8.5%)
log Income	0.2751 (47.2%)	Lagged log # branches	0.0236 (4.0%)
log Population	0.0957 (16.4%)	Industry Shares	0.0836 (14.3%)

Panel C: Spatial Autoreggressive Process of u_{mt}

Parameter	Estimate (s.e.)	Parameter	Estimate (s.e.)
ρ ($<$ 200 *miles*)	0.3573 (0.0229)***	ρ (400 *to* 1000 *miles*)	0.1115 (0.0544)*
ρ (200 *to* 400 *miles*)	0.2699 (0.0321)***	ρ ($>$ 1000 *miles*)	−0.1510 (0.2883)

Standard errors in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
The omitted two-digit industry in Employment and Establishment shares is Agriculture, Forestry, Fishing, and Hunting.

variance of the diversifiable risk (not reported here), most of the heterogeneity across counties in diversifiable risk is captured by county fixed effects. After controlling for these fixed effects, the contribution of time-varying observables to diversifiable risk is small and not statistically significant.

Figures 5, 6, and 7 present the cross-sectional distributions of expected log-deposits-per-branch, systematic risk, and diversifiable risk based on the estimates of the factor model. These cross-sectional distributions have been very stable over the whole sample period. Furthermore, these variables are very persistent over time for almost every county, that is, counties with high levels of systematic or diversifiable risk in 1996 also have high levels of risk in 2006.

The levels of systematic and diversifiable deposit risk are quite substantial for most counties. In the county-level distributions, the 10th and 90th percentiles are 0.6 and 2.3 percentage points for the systematic risk, and 1.1 and 3.1 percentage points for the diversifiable risk. To get a better idea of the significance of this level of deposit risk, it is useful to take into account that a 1 percentage point reduction in this risk typically implies more than 1 percentage point increase in a bank's rate of ROE. We illustrate this point using a simple model in the Appendix. Therefore, differences between banks' geographic diversification may explain a substantial part of their differences in profitability.

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FIGURE 5

CROSS-SECTIONAL DISTRIBUTION OF EXPECTED LOG-DEPOSITS-PER-BRANCH

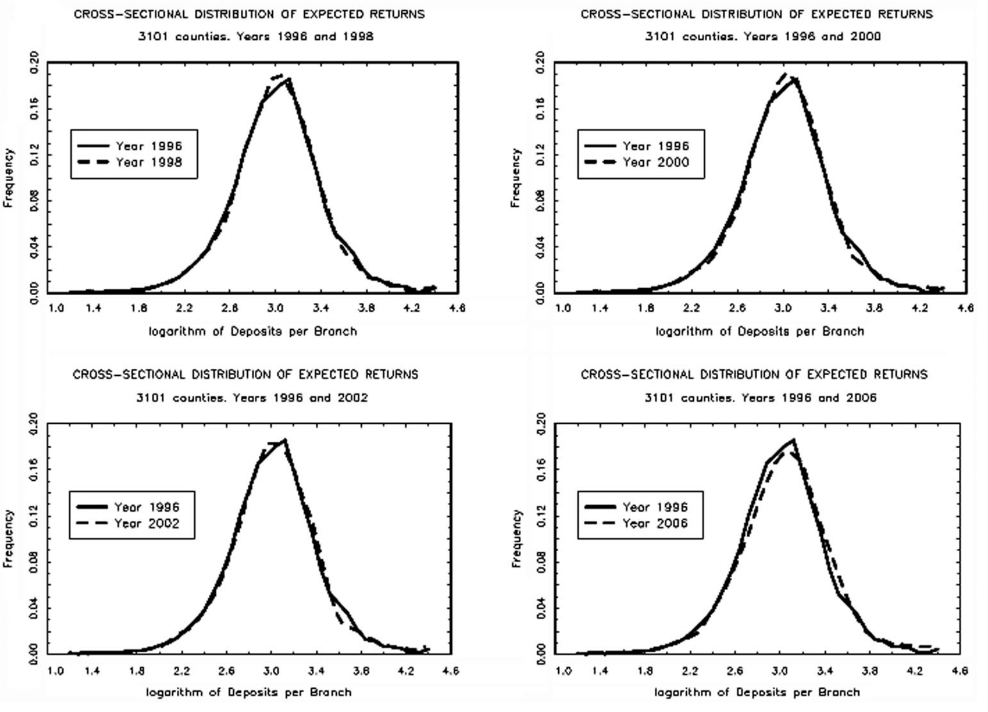

FIGURE 6

CROSS-SECTIONAL DISTRIBUTIONS OF DIVERSIFIABLE RISK

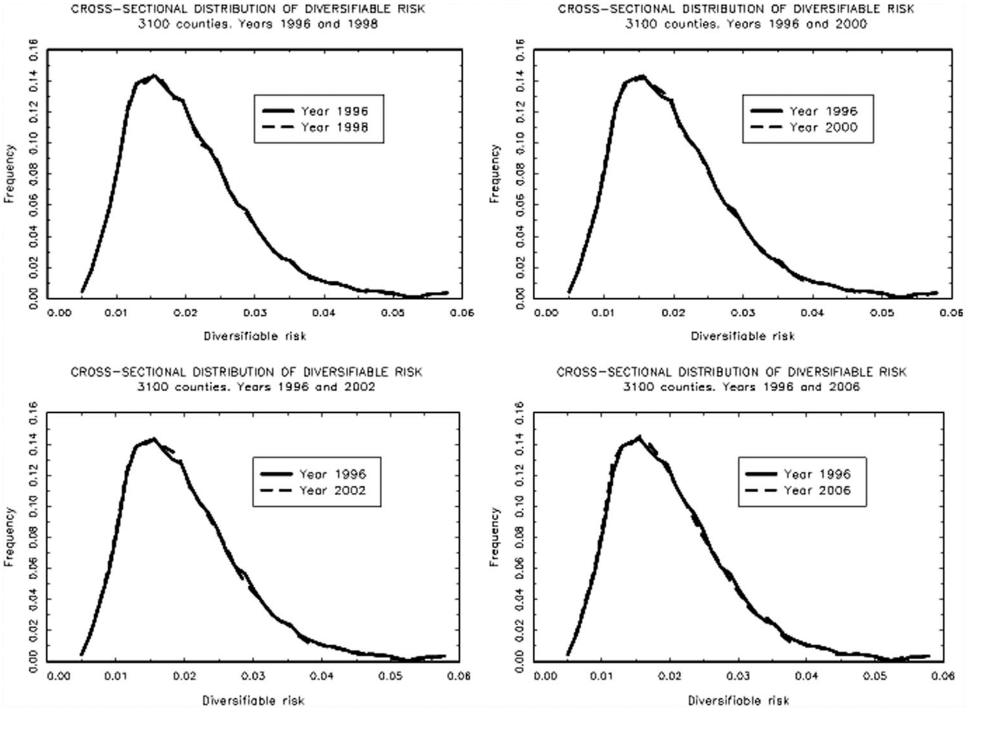

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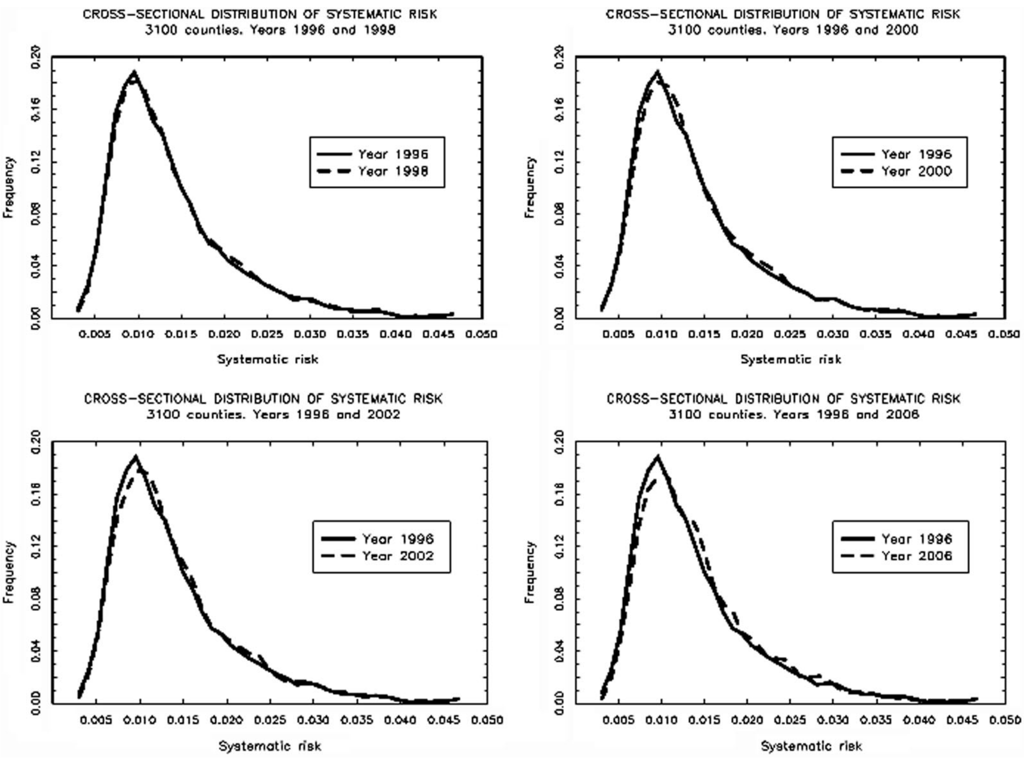
FIGURE 7

CROSS-SECTIONAL DISTRIBUTIONS OF SYSTEMATIC RISK



5. Evolution of bank geographic risk from deposits

■ In this section, we use the estimates of the factor model to determine (i) the extent to which banks *can* diversify their geographic risk and (ii) the extent to which banks *did* diversify their risk.

□ **Possibilities of geographic risk diversification: efficient frontiers.** We start presenting the possibilities for GRD available to banks before and after RN. We use our estimates of $\boldsymbol{\mu}_t$ and $\boldsymbol{\Omega}_t$ above to construct efficient frontiers for each state in 1995 before banks could take advantage of RN, and a single efficient frontier in 1995 assuming banks can locate branches anywhere in the United States. A bank *portfolio* is its branch network $\mathbf{n}_{it}$. Let $\mathbf{w}_{it} \equiv \{w_{imt} : m = 1, 2, \ldots, M\}$ be the vector of asset shares in the portfolio of bank i such that $w_{imt} \equiv n_{imt}/(\sum_{m'=1}^{M} n_{im't})$. The return of a branch is measured by the logarithm of deposits-per-branch. By *expected return* and *risk* of a bank branch portfolio, we mean $R_{it} \equiv \mathbf{w}'_{it}\ \boldsymbol{\mu}_t$ and $S_{it} \equiv \sqrt{\mathbf{w}'_{it}\ \boldsymbol{\Omega}_t\ \mathbf{w}'_{it}}$, respectively. A portfolio lying on the efficient frontier represents the best possible *expected return* (ER) for given level of risk. For the moment, the construction of these efficient frontiers is based on the assumption that banks can open "many" branches in a state and locate them optimally throughout all of the counties. This efficient frontier informs us of the possibilities of diversification only for large banks.[23]

(a) Prior to Riegle-Neal. Figure 8 presents the efficient frontiers for each of the states, with Risk on the horizontal axis and Expected Return (ER) on the vertical axis. We have ordered

[23] More precisely, in the construction of these frontiers, we assume that the weights w_{imt} are continuous variables. This is a good approximation to the actual choice of a bank only when its total number of branches is large.

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FIGURE 8

EFFICIENT FRONTIERS IN 1995

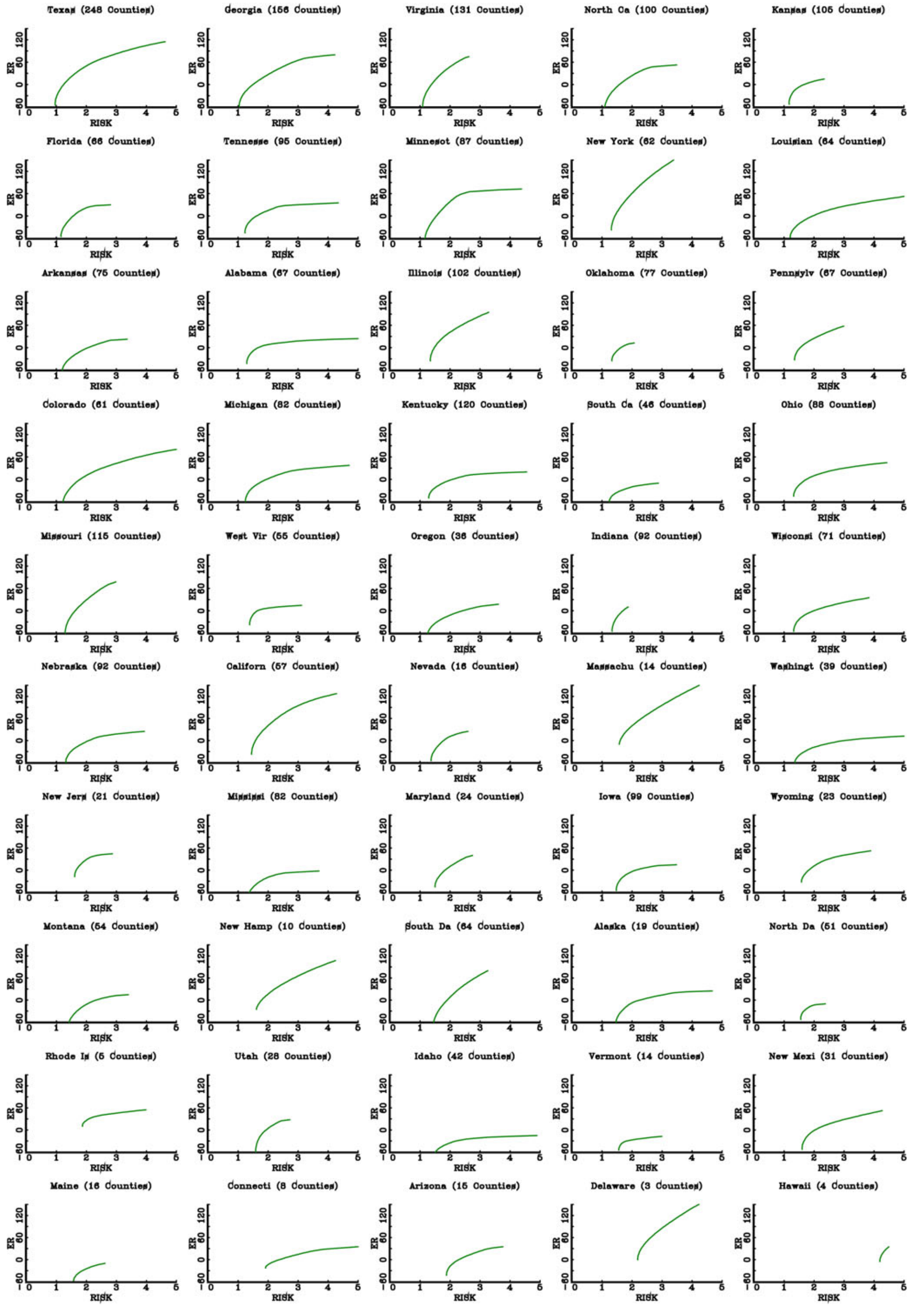

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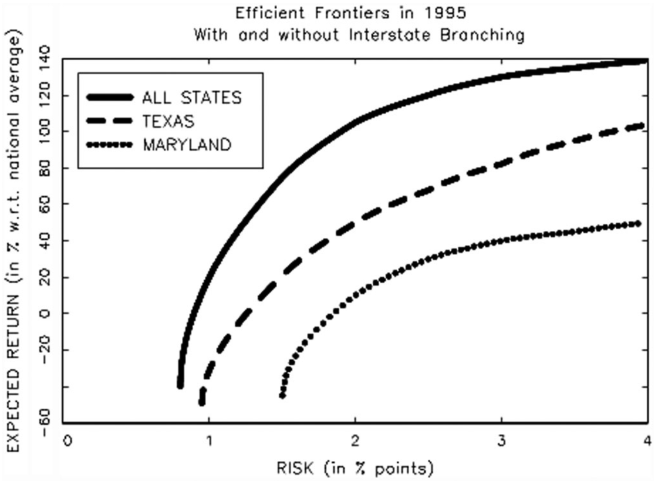
FIGURE 9

EFFICIENT FRONTIERS IN 1995 WITH AND WITHOUT INTERSTATE BRANCHING



states according to their maximum return-to-risk (RR) ratios. The figure reveals very significant cross-state heterogeneity in the pre-RN frontiers. The observed heterogeneity implies that the possibilities for GRD for very large banks differed significantly across states. Therefore, in some states large banks could easily achieve a diverse portfolio of branches whereas in others, they would have been constrained by the limitations of the pre-RN regulations.

(b) Post-Riegle-Neal. Figure 9 plots the 1995 efficient frontier assuming banks can locate branches anywhere in the United States. The comparison of this frontier with the pre-RN frontier of a small state like Maryland shows that the possibilities for risk diversification improved dramatically for large banks located in small states. The comparison with a large state like Texas shows more moderate improvements. Table 5 reports the percentage change in maximum expected return-to-risk and minimum risk in the efficient frontier for each state resulting from RN. On average, the risk of an efficient portfolio declined 0.6 percentage points,[24] which represents about a 1 standard deviation decline relative to the efficient risk in 1995. The improvement is particularly important for states with restrictive frontiers prior to deregulation.

□ **Geographic risk diversification possibilities—small banks.**

(a) Prior to Riegle-Neal. The efficient frontiers presented above describe the GRD possibilities only for large banks, as their construction is based on the assumption that banks can open a continuum of branches and locate them optimally throughout all of the counties in a given state. Most banks do not have a very large number of branches and the frontier for a continuum of branches might not be a realistic constraint for them. In this section, we seek evidence on the possibilities of GRD pre-RN for banks with a relatively small number of branches and with a "home-county bias." Our evidence is based on the following "thought experiment." We suppose that a bank has a single branch in county m. We then suppose that this bank can open $n - 1$ more branches anywhere within the state, but that it must maintain its original branch in county m. We suppose that these branches are added sequentially, with each additional branch added in such a way as to maximize the expected return-to-risk ratio taking as *given* the location of the previous existing branches. We then ask the following questions: (i) What is the maximum expected return-to-risk ratio that this bank can reach when it adds $n - 1$ branches optimally?

[24] For each county, we calculate the difference in levels of risk before and after RN, and then we average across counties.

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TABLE 5 Change in Efficient Frontiers after Riegle-Neal: % Change in Maximum Expected Return-to-Risk Ratio (MaxRR) and Minimum Risk (MinRisk) (States sorted by MaxRR in 1995)

	Year 1995		% Change			Year 1995		% Change	
State (# counties)	Maximum RR	Minimum Risk	Maximum RR	Minimum Risk	State (# counties)	Maximum RR	Minimum Risk	Maximum RR	Minimum Risk
Texas (248)	805	0.40%	42%	−29%	Pennsylvania (67)	452	0.69%	153%	−59%
Missouri (115)	668	0.45%	71%	−36%	Vermont (14)	447	0.70%	155%	−59%
Georgia (156)	647	0.47%	76%	−39%	North Dakota (51)	442	0.68%	158%	−58%
N. Carolina (100)	646	0.47%	77%	−39%	Michigan (82)	415	0.69%	175%	−59%
Louisiana (64)	629	0.49%	81%	−41%	Montana (54)	408	0.73%	179%	−61%
Virginia (131)	629	0.48%	81%	−40%	California (57)	404	0.82%	182%	−65%
Wisconsin (71)	625	0.48%	82%	−40%	New Hampshire (10)	368	0.93%	210%	−69%
Kentucky (120)	620	0.51%	84%	−43%	New Mexico (31)	350	0.87%	226%	−67%
Illinois (102)	593	0.53%	92%	−46%	Colorado (61)	339	0.88%	236%	−68%
Arkansas (75)	584	0.52%	95%	−44%	Idaho (42)	320	0.90%	257%	−68%
Oklahoma (77)	583	0.53%	96%	−46%	Maine (16)	317	0.91%	260%	−68%
West Virginia (55)	583	0.55%	96%	−48%	Alaska (19)	314	0.97%	263%	−70%
Alabama (67)	582	0.54%	96%	−47%	Oregon (36)	307	0.98%	271%	−71%
Mississippi (82)	568	0.52%	101%	−45%	Wyoming (23)	301	1.06%	279%	−73%
Kansas (105)	565	0.55%	102%	−48%	New Jersey (21)	297	1.08%	283%	−73%
Florida (66)	562	0.56%	103%	−49%	Maryland (24)	290	1.03%	293%	−72%
Tennessee (95)	518	0.60%	120%	−52%	Utah (28)	286	0.99%	299%	−71%
New York (62)	509	0.64%	124%	−55%	Delaware (3)	284	1.25%	301%	−77%
South Dakota (64)	498	0.60%	129%	−52%	Connecticut (8)	277	1.16%	313%	−75%
Nebraska (92)	496	0.61%	130%	−53%	Arizona (15)	274	1.18%	316%	−76%
S. Carolina (46)	485	0.62%	135%	−54%	Washington (39)	267	1.10%	327%	−74%
Indiana (92)	482	0.64%	137%	−55%	Massachusetts (14)	248	1.37%	359%	−79%
Minnesota (87)	479	0.62%	138%	−54%	Nevada (16)	223	1.34%	412%	−79%
Ohio (88)	473	0.66%	141%	−57%	Rhode Island (5)	219	1.65%	421%	−83%
Iowa (99)	465	0.66%	146%	−56%	Hawaii (4)	118	3.12%	864%	−91%

Note: Columns "% Change" report the percentage change in maximum possible return-to-risk ratio (MaxRR) and minimum possible risk (MinRisk) between the frontiers without and with interstate branching.

(ii) What is the minimum level of risk that this bank can achieve when it adds $n-1$ branches optimally?

We implement this "thought experiment" for every US county using the expected return and variance matrix of 1995. Then we construct the following statistics at the state level: the median of the maximum expected return-to-risk ratio, and the median of the minimum possible risk level with $n=1$, $n=5$, and $n=10$ branches, respectively. For the sake of comparison, we also report the minimum risk with a continuum of branches, that is, MinRisk. We compare these statistics between states to learn about heterogeneity in the possibilities of GRD for small banks prior to RN. Table 6 presents statistics for Minimum Risk. For almost every state, small banks can achieve significant benefits from within-state GRD. In every state, with the exception of Hawaii and New Hampshire, opening a second branch reduces the minimum risk by more than 1.0 percentage point, and in most states by more than 1.5 percentage points. There is further benefit to adding more branches, but this benefit declines rapidly with the number of branches and becomes almost negligible when this number is greater than 10, even in large states like Texas. Second, there are significant differences across states in the benefits of within-state GRD for small banks. For instance, the reduction in minimum risk associated with a network expansion from one to five branches is less than one percentage point for states such as Hawaii (0.5), Rhode Island (0.5), Delaware (0.8), Maine (0.9), or New Hampshire (0.98), but is above two percentage points for Colorado (2.4), Alaska (2.3), or Virginia (2.0).

(b) Post-Riegle-Neal. To study the possibilities for GRD post-RN for smaller banks, we repeat the thought experiment performed above, but now assume that in addition to being able to locate inside their home state, banks can expand beyond state borders. This provides banks with more options for diversifying their risk. For simplicity of calculation, we assume that

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TABLE 6 Feasible Minimum Risk for Small Banks Before Riegle-Neal: (States sorted by Maximum Return-to-Risk Ratio in the Efficient Frontier in 1995)

	Minimum Risk with n Branches(%)[(a)]					Minimum Risk with n Branches (%)[(a)]			
State (# counties)	n = 1	n = 5	n = 10	MinRisk[(b)]	State (# counties)	n = 1	n = 5	n = 10	MinRisk[(b)]
Texas (248)	2.39	0.74	0.57	0.40	Pennsylvania (67)	1.97	0.87	0.77	0.69
Missouri (115)	2.23	0.69	0.56	0.45	Vermont (14)	2.10	0.82	0.73	0.70
Georgia (156)	2.64	0.75	0.58	0.47	North Dakota (51)	2.13	0.87	0.75	0.68
N. Carolina (100)	2.15	0.69	0.55	0.47	Michigan (82)	2.40	0.91	0.78	0.69
Louisiana (64)	2.39	0.76	0.59	0.49	Montana (54)	2.74	1.01	0.82	0.73
Virginia (131)	2.73	0.80	0.61	0.48	California (57)	2.70	1.02	0.89	0.82
Wisconsin (71)	2.17	0.68	0.56	0.48	New Hampshire (10)	1.97	0.99	0.95	0.93
Kentucky (120)	2.45	0.79	0.62	0.51	New Mexico (31)	2.71	1.06	0.93	0.87
Illinois (102)	2.26	0.79	0.65	0.53	Colorado (61)	3.57	1.21	1.01	0.88
Arkansas (75)	2.23	0.75	0.63	0.52	Idaho (42)	3.04	1.18	0.99	0.90
Oklahoma (77)	2.17	0.74	0.62	0.53	Maine (16)	1.95	1.00	0.93	0.91
West Virginia (55)	2.21	0.77	0.65	0.55	Alaska (19)	3.55	1.24	1.03	0.97
Alabama (67)	2.41	0.83	0.64	0.54	Oregon (36)	2.45	1.17	1.03	0.98
Mississippi (82)	2.24	0.78	0.61	0.52	Wyoming (23)	2.75	1.25	1.10	1.06
Kansas (105)	2.54	0.81	0.66	0.55	New Jersey (21)	2.72	1.21	1.12	1.08
Florida (66)	2.55	0.80	0.65	0.56	Maryland (24)	2.83	1.16	1.08	1.03
Tennessee (95)	2.16	0.80	0.68	0.60	Utah (28)	2.75	1.15	1.04	0.99
New York (62)	2.03	0.82	0.70	0.64	Delaware (3)	2.09	1.25	1.25	1.25
South Dakota (64)	2.63	0.84	0.68	0.60	Connecticut (8)	2.88	1.27	1.19	1.16
Nebraska (92)	2.45	0.88	0.72	0.61	Arizona (15)	2.60	1.30	1.20	1.18
S. Carolina (46)	2.15	0.78	0.68	0.62	Washington (39)	2.44	1.27	1.15	1.10
Indiana (92)	2.27	0.83	0.71	0.64	Massachusetts (14)	2.48	1.43	1.39	1.37
Minnesota (87)	2.29	0.84	0.72	0.62	Nevada (16)	3.25	1.55	1.41	1.34
Ohio (88)	2.09	0.86	0.74	0.66	Rhode Island (5)	2.17	1.65	1.66	1.65
Iowa (99)	2.52	0.89	0.76	0.66	Hawaii (4)	3.67	3.17	3.15	3.12

Note (a): We assume that banks can only expand within their home state and minimize risk when adding a new branch. Note (b): MinRisk represents the minimum risk with a continuum of branches. It is the same as minimum risk in Table 5 above.

banks can only expand to contiguous states. This is a lower bound on the benefits from RN, because RN allows banks not only to expand into contiguous states, but into any state in the country.

Table 7 presents the percentage difference in maximum expected return-to-risk ratio (MaxRR) and minimum risk (MinRisk) pre-RN and post-RN for a bank with only five branches. The percentage changes in MaxRR and MinRisk are calculated for each county and the reported numbers are the median values of counties for each state. As in the case of large banks, we also find substantial heterogeneity in the effects of RN on the possibilities of GRD of small banks. In some states, there is little benefit to being able to expand to neighboring states: Texas (change in MaxRR is 5.8%, and change in MinRisk is −6.7%), California (8.1% and −9.2%), or Wisconsin (3.6% and −2.3%). However, the effect in other states is very considerable: Massachusetts (81.3% and −46.8%), Nevada (80.3% and −32.2%), Maryland (75.7% and −39.5%), Delaware (58.8% and −40.8%), or Rhode Island (34.9% and −32.2%).

□ **Actual bank portfolios.** So far, we have talked only about the possibilities for GRD in different states before and after RN. Here, we study *actual* bank portfolios in an effort to learn about the extent to which banks were diversified at the time of RN and whether this is the result of the constraints imposed on expansion prior to its implementation.

In Figures 10 and 11, we present the cross-sectional distributions of banks' expected return and risk, respectively, in years 1995 and 2006. Using the vector of means and the variance matrix of deposits-per-branch of 1995, we obtain the expected return, R_i, and the risk, S_i, for each bank in 1995, and present their empirical distribution. Similarly, we derive the empirical distributions

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TABLE 7 Effect of RN on the Possibilities of GRD of Small Banks

State (# counties)	TEMaxRR %Δ RR	TEMinRisk %Δ risk	State (# counties)	TEMaxRR %Δ RR	TEMinRisk %Δ risk
Texas (248)	5.8	−6.7	Pennsylvania (67)	31.1	−20.6
Missouri (115)	16.9	−13.1	Vermont (14)	12.7	−8.8
Georgia (156)	8.1	−7.2	North Dakota (51)	21.0	−17.7
N. Carolina (100)	9.3	−7.4	Michigan (82)	41.8	−24.0
Louisiana (64)	21.1	−12.8	Montana (54)	29.1	−24.5
Virginia (131)	11.7	−10.7	California (57)	8.1	−9.2
Wisconsin (71)	3.6	−2.3	New Hampshire (10)	20.1	−20.1
Kentucky (120)	21.3	−19.2	New Mexico (31)	49.1	−29.0
Illinois (102)	26.0	−24.5	Colorado (61)	58.5	−35.6
Arkansas (75)	25.0	−17.0	Idaho (42)	33.3	−21.5
Oklahoma (77)	21.6	−16.7	Maine (16)	39.8	−18.0
West Virginia (55)	4.4	−6.5	Alaska (19)	0.0	0.0
Alabama (67)	11.6	−13.9	Oregon (36)	40.1	−25.4
Mississippi (82)	14.8	−10.1	Wyoming (23)	54.9	−38.5
Kansas (105)	10.6	−11.6	New Jersey (21)	52.8	−32.9
Florida (66)	10.7	−12.2	Maryland (24)	75.7	−39.5
Tennessee (95)	31.9	−25.5	Utah (28)	47.6	−26.0
New York (62)	12.7	−13.2	Delaware (3)	58.8	−40.8
South Dakota (64)	10.0	−9.1	Connecticut (8)	41.5	−29.1
Nebraska (92)	27.8	−22.8	Arizona (15)	45.8	−34.9
S. Carolina (46)	16.9	−14.4	Washington (39)	22.3	−17.9
Indiana (92)	22.9	−17.6	Massachusetts (14)	81.3	−46.8
Minnesota (87)	34.8	−24.7	Nevada (16)	80.3	−39.7
Ohio (88)	22.4	−16.8	Rhode Island (5)	34.9	−32.2
Iowa (99)	41.5	−28.2	Hawaii (4)	0.0	0.0

This table reports median (across counties) percentage changes in expected return-to-risk ratio and risk in the thought experiment for banks with five branches before and after the RN Act.
(a): "TEMaxRR": Thought experiment when a bank sequentially adds branches to maximize expected return-to-risk ratio.
(b): "TEMinRisk": Thought experiment when a bank sequentially adds branches to minimize risk.
(c): $\%\Delta RR = (post\_RR - pre\_RR)/pre\_RR * 100$. This percentage change is calculated for each county. The reported number is the median value of counties for each state.
(d): $\%\Delta Risk = (post\_Risk - pre\_Risk)/pre\_Risk * 100$. This percentage change is calculated for each county. The reported number is the median value of counties for each state.

FIGURE 10

DISTRIBUTION OF BANKS' EXPECTED LOG-DEPOSITS-PER-BRANCH: 1995 AND 2006

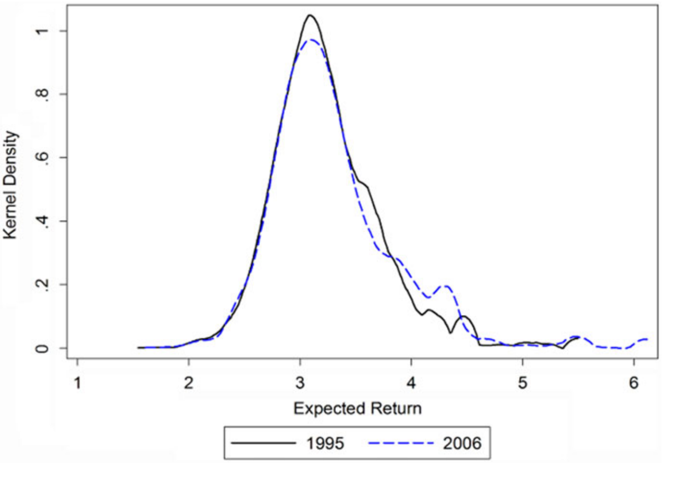

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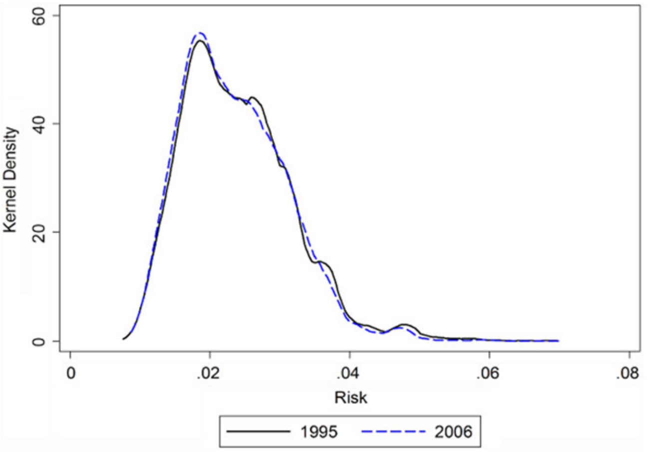
FIGURE 11

DISTRIBUTIONS OF BANKS' RISK OF DEPOSITS: 1995 AND 2006



of banks' expected return and risks in 2006. The comparison of the 1995 distributions at the bank level with the corresponding distributions at the county level (in Figures 5 to 7) shows that, despite the modest geographic spread of bank networks in 1995, bank risk is substantially smaller than county risk (i.e., their medians are 2.4% and 3.5%, respectively). In contrast, the distributions of expected log-deposits-per-branch at bank and county level are very similar. Figure 10 shows some improvement in expected log-deposits-per-branch from 1995 to 2006, that is, the median value goes from 3.17 to 3.19, an improvement of two percentage points. However, Figure 11 shows almost no reduction in risk, that is, the median value goes from 0.0230 to 0.0226, a reduction in 0.04 percentage points.

The evidence presented so far suggests that bank deposit risk decreased very little between 1995 and 2006. We are interested in determining what part of the change in bank risk can be attributed to RN and what part stems from other factors. In principle, it is possible that exogenous changes in the distribution of county risk, or within-state changes in bank networks, may have offset the effects of RN on banks' risk. To disentangle the contribution of RN, in what follows we present results from a counterfactual decomposition of the change in the empirical distribution of bank risk and expected log-deposits-per-branch between 1995 and 2006.

A cross-sectional distribution of banks' risk, either factual or counterfactual, can be described as a vector of banks' risks $\mathbf{S} \equiv \{S_i : i \in I\}$ where I is a set of banks, and S_i is the risk of bank i. Because the risk of bank i is determined by the function $S_i = \sqrt{\mathbf{n}_i' \ \mathbf{\Omega} \ \mathbf{n}_i}$, we have that we can represent a cross-sectional distribution of banks' risks as a function $\mathbf{S} = f(\mathbf{\Omega}, I, \mathbf{n})$. If the values of the matrix $\mathbf{\Omega}$, the set of banks I, and the banks' branch networks $\{\mathbf{n}_i\}$ correspond to their actual values in a particular year t, then we have the factual distribution of risks in that year, that is, $\mathbf{S}_t = f(\mathbf{\Omega}_t, I_t, \mathbf{n}_t)$. Otherwise, we have a counterfactual distribution of risks. Using function $f(.)$, we can decompose the actual change in the distribution of banks' risks between years 1995 and 2006, $\mathbf{S}_{06} - \mathbf{S}_{95}$, into the contribution of three counterfactual changes:

$$\begin{aligned} \mathbf{S}_{06} - \mathbf{S}_{95} = & \left[f(\mathbf{\Omega}_{06}, I_{95}, \mathbf{n}_{95}) - f(\mathbf{\Omega}_{95}, I_{95}, \mathbf{n}_{95})\right] && \Rightarrow \text{Contribution of change in } \mathbf{\Omega} \\ & + \left[f\left(\mathbf{\Omega}_{06}, I_{06}^{IN}, \mathbf{n}_{06}^{IN}\right) - f(\mathbf{\Omega}_{06}, I_{95}, \mathbf{n}_{95})\right] && \Rightarrow \text{Contribution of within-state expansion} \\ & + \left[f(\mathbf{\Omega}_{06}, I_{06}, \mathbf{n}_{06}) - f\left(\mathbf{\Omega}_{06}, I_{06}^{IN}, \mathbf{n}_{06}^{IN}\right)\right] && \Rightarrow \text{Contribution of out-of-state expansion} \end{aligned} \tag{6}$$

This decomposition captures three different *ceteris paribus* effects. The first term measures the contribution of the change in matrix $\mathbf{\Omega}$ between 1995 and 2006. The term $f(\mathbf{\Omega}_{06}, I_{95}, \mathbf{n}_{95})$ is the counterfactual distribution that we would observe if the set of banks and their branch networks

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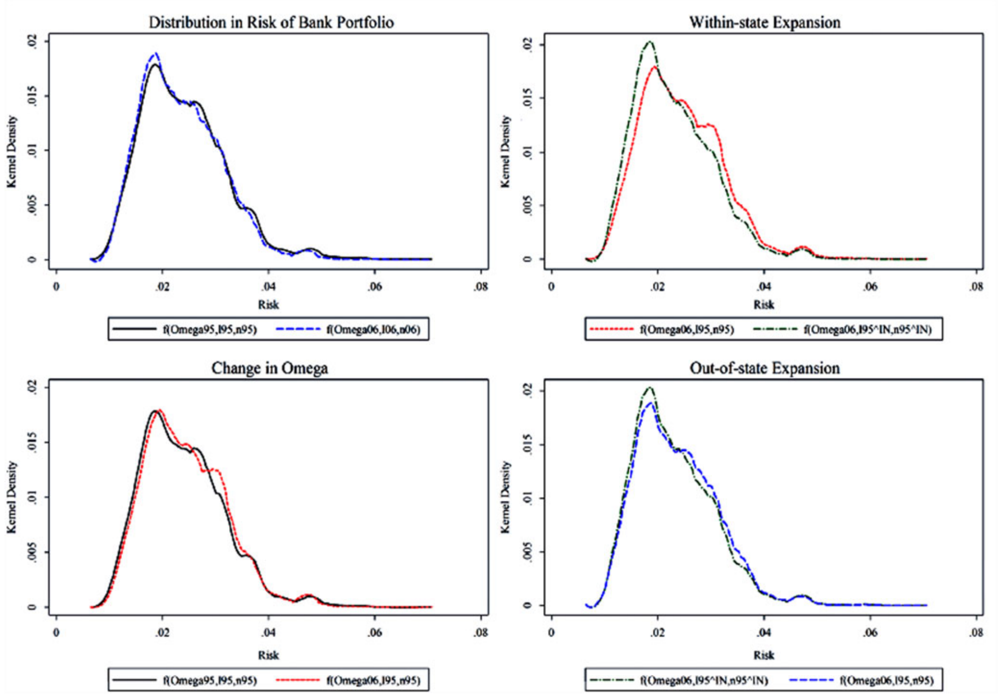
FIGURE 12

DECOMPOSITION OF CHANGE IN DISTRIBUTION OF BANKS' RISK: 1995–2006



were the ones in 1995, but we had the variance matrix of risks of 2006. Therefore, the difference $[f(\mathbf{\Omega}_{06}, I_{95}, \mathbf{n}_{95}) - f(\mathbf{\Omega}_{95}, I_{95}, \mathbf{n}_{95})]$ measures the *ceteris paribus* contribution of the change in $\mathbf{\Omega}$. The second term measures the *ceteris paribus* effect of within-state branch expansion and mergers. In the counterfactual distribution $f(\mathbf{\Omega}_{06}, I_{06}^{IN}, \mathbf{n}_{06}^{IN})$, the arguments I_{06}^{IN} and $\mathbf{n}_{06}^{IN}$ represent the set of banks and the vector of branch networks in 2006, respectively, if we eliminate any bank expansion outside the home state, that is, we eliminate mergers between banks with different home states, and "close" branches opened in states other than the home state of the bank. The third term captures the *ceteris paribus* effect of out-of-state branch expansion and mergers. This is because the difference between $\{I_{06},\mathbf{n}_{06}\}$ and $\{I_{06}^{IN},\mathbf{n}_{06}^{IN}\}$ captures banks' expansion outside their home state either through mergers of *de novo* branching.[25]

Results are presented in Figures 12 and 13 for the distributions of risk and expected log-deposits-per-branch, respectively. The figure on the top left figure shows the actual change in the distribution. The other three figures present the contribution to the actual change of the variation in the omega matrix, within-state expansion, and out-of-state expansion, respectively. These figures show that out-of-state branch expansion did not have any contribution to the reduction in bank risk but contributed to increase expected log-deposits-per-branch. Almost all of the small reduction in risk comes from within-state branch expansion. During the post-RN period, a substantial fraction of banks reduced their risk by expanding geographically within the limits of their states. As we have shown above, for most states (except a group of small states predominantly located in the East Coast) in 1995, there were important benefits from within-state GRD that had not been exploited by most banks. The evidence suggests that between 1995–2006, many banks in these states have taken advantage of the possibilities for GRD afforded them through within-state expansion. As

[25] For the construction of the counterfactual sets of banks and branch networks $\{I_{06}^{IN},\mathbf{n}_{06}^{IN}\}$, we need to make some assumptions. We describe these assumptions in the Appendix.

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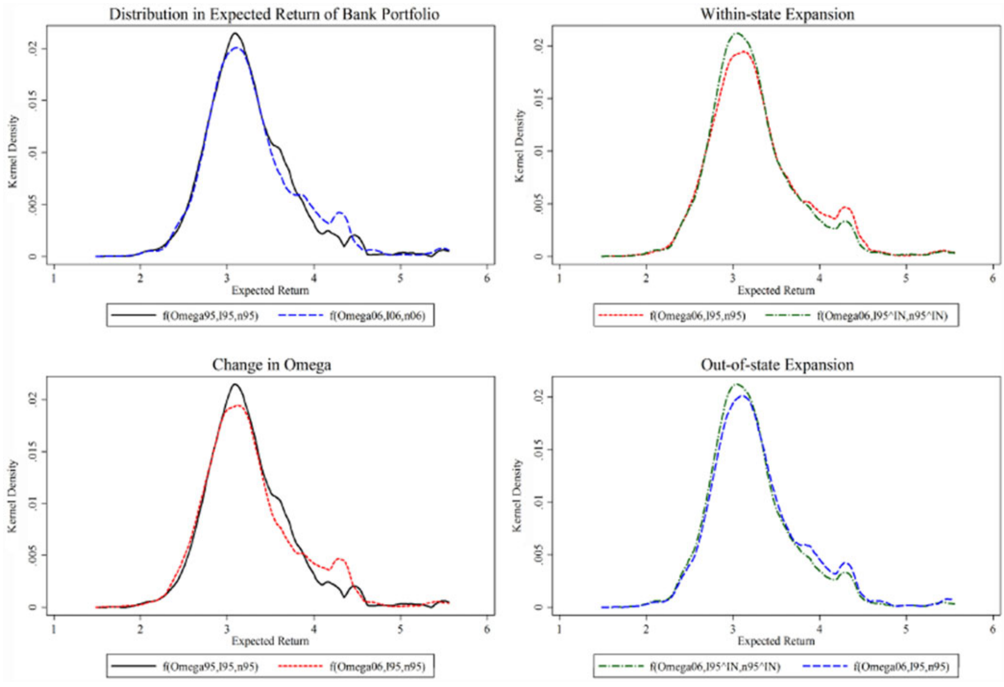
FIGURE 13

DECOMPOSITION OF CHANGE IN DISTRIBUTION OF BANKS' EXPECTED DEPOSITS-PER-BRANCH: 1995–2006



illustrated in Figure 1, this process of within-state bank expansion and consolidation via mergers is not new, and has been an ongoing process since the 1980s.

In Figures 14 and 15, we present the same results, but now weighting by deposit. This exercise is important because, as we have shown above, following RN, deposits became much more concentrated in a small number of banks. One possibility is that, whereas small banks remain small and undiversified geographically, larger banks with the majority of deposits are in fact the ones that took advantage of the diversification possibilities afforded by RN. If this were the case, then policy makers might be able to claim that RN did have a positive influence on the geographic risk levels of banks.

Overall we find that following RN: (i) large banks have increased very substantially their expected log-deposits-per-branch, regardless of their initial values in 1995; and (ii) large banks have contributed to reduce the median level of risk. Decomposing the change in risk, we find that large banks expanded within-state to reduce geographic risk, but expanded out-of-state in a way to *increase* risk, negating the motivation for RN. The purpose of large banks expanding out-of-state would appear to be to achieve higher expected log-deposits-per-branch. For expansion within-state, expected log-deposits-per-branch actually become more concentrated on lower values, suggesting that some large banks expand within-state to achieve GRD at the cost of lowering expected log-deposits-per-branch.

6. A structural model of bank choice of branch network

■ We have shown that RN implied a substantial improvement in the possibilities of GRD for many banks with headquarters in small states, but that most of these banks did not take advantage of these possibilities. One explanation for this finding is that banks are not seriously concerned about geographic diversification of deposit risk. An alternative explanation is that other factors,

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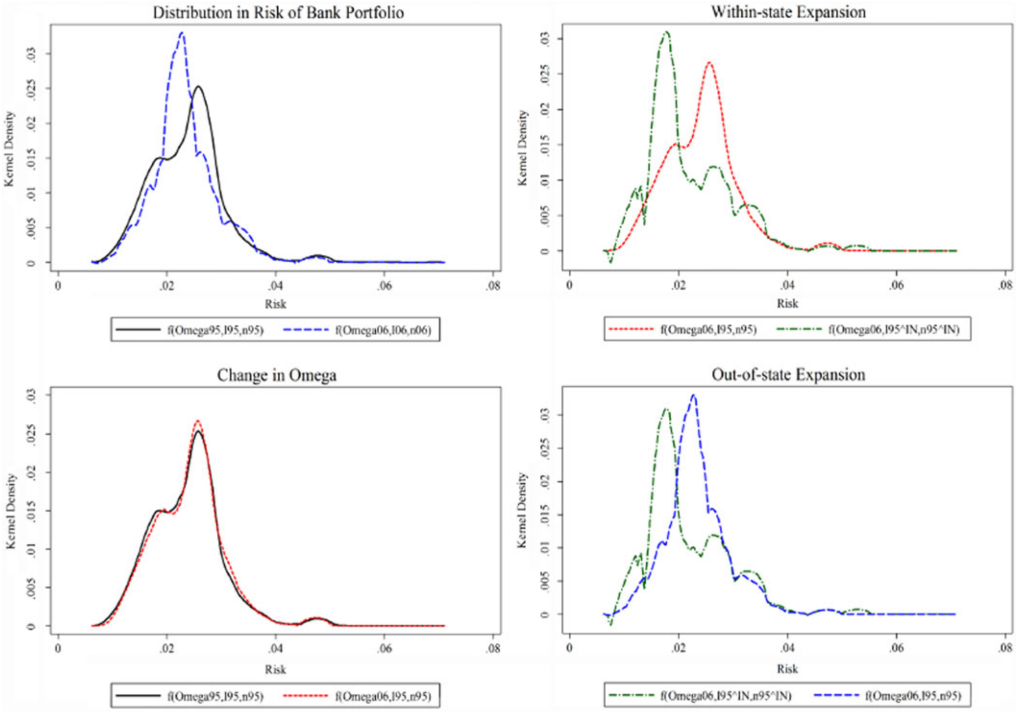
FIGURE 14

DECOMPOSITION OF CHANGE IN DISTRIBUTION OF RISK: 1995–2006
Each bank observation is weighted by the bank total volume of deposits



such as diseconomies of scale, economies of density, merging costs, and local market power have counterbalanced banks' concern for GRD. In this section, we propose and estimate a structural model of competition between branch networks and use this model to identify banks' concern for GRD separately from other factors that influence branch-network expansion.[26]

□ **Bank competition in a local market.** A first component of our model deals with competition between banks at the level of local markets (i.e., counties). The number of branches of each bank in a local market is determined in the game of network competition that we describe below, and it is exogenous (i.e., predetermined) in this game of local market competition. Branches compete for the supply of deposits from households and businesses in the market. The Nash equilibrium in this model of local competition implies equilibrium functions that relate the deposits and the profits of a bank in a local market with the number of branches, their ownership structure, and exogenous market characteristics, that is, $D_{imt} = f_d(n_{imt}, \mathbf{n}_{mt}, X_{mt})$ and $\pi_{imt} = f_\pi(n_{imt}, \mathbf{n}_{mt}, X_{mt})$. For the purpose of this article, we are interested in the equilibrium functions f_d and f_π more than in the structural estimation of demand and supply of deposits at the local market level. There are different models of competition that provide similar forms of these equilibrium functions. We propose here a Cournot model with multiple branches, linear consumer supply of deposits, and a convex cost function. The predictions of this model are consistent with the evidence shown in Section 3 on diseconomies of scale at the branch level.

The consumer supply of deposits in market m at period t is described by the equation $r_{mt} = \alpha_{mt} + \beta\ D_{mt}$, where D_{mt} is the total amount of deposits in the market, r_{mt} represents the

[26] Corbae and D'Erasmo (2011) have also proposed a model of bank competition at two different geographic levels, regional and national. They use this model to study the effects of different regulations on bank failure.

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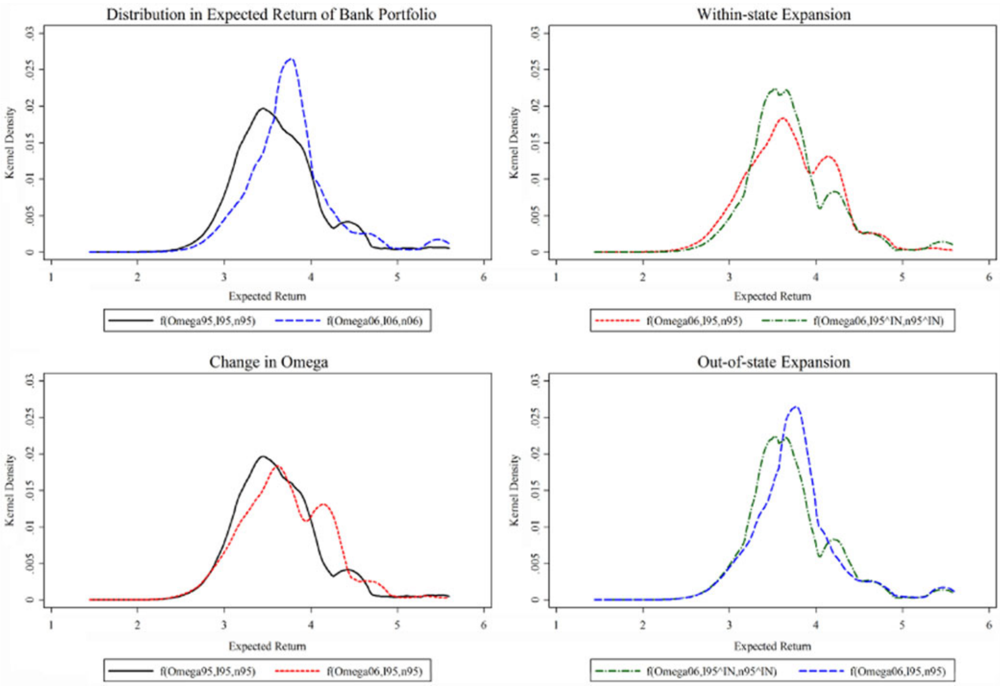
FIGURE 15

DECOMPOSITION OF CHANGE IN DISTRIBUTION OF EXPECTED LOG-DEPOSITS-PER-BRANCH: 1995-2006
Each bank observation is weighted by the bank total volume of deposits



interest rate of deposits, α_{mt} is an exogenous shifter, and $\beta > 0$ is a parameter that represents the slope of the supply curve. Let n_{imt} and D_{imt} be the number of stores and the total amount of deposits of bank i in market m. The variable profit of this bank is:

$$\pi_{imt} = (p_{mt} - r_{mt})\ D_{imt} - C_{mt}\,(D_{imt}, n_{imt})\,. \tag{7}$$

The term p_{mt} represents the return from the best lending options in this market, and we assume that it is exogenously given. The function $C_{mt}(D, n)$ represents the variable cost of the bank for managing a volume of deposits D using n branches. We consider the following specification of this cost function: $C_{mt}(D, n) \equiv \gamma_{mt}\ D + [\delta(n)/2]\ D^2$, where γ_{mt} is an exogenous cost shifter, and $\delta(n)$ is a positive-valued and decreasing function that captures diseconomies of scale at the branch level, that is, for the same volume of deposits, total variable costs decline with the number of branches.

Banks active in the market take their stores as given and compete a la Nash-Cournot by choosing the amount of deposits D_{imt} that maximizes profits in the local market. In the equilibrium of this game, a bank's deposits and profits depend on its own number of branches and on the number of branches of other banks. It is straightforward to show that the equilibrium amount of deposits of a bank is[27]

$$D^*_{imt} = \left(\frac{\widetilde{p}_{mt}}{I^*_{mt} + 1}\right)\ \left(\frac{1}{1 + \widetilde{\delta}(n_{imt})}\right), \tag{8}$$

[27] The first-order condition for profit maximization implies that $(p - r - \gamma) - \beta D_i - \delta(n_i)D_i = 0$, or solving for deposits, $D_i = (\frac{p-r-\gamma}{\beta})\,(\frac{1}{1+\delta(n_i)/\beta})$. Aggregating over banks and solving for the equilibrium value of market deposits, we obtain that $D = (\frac{p-\alpha-\gamma}{\beta})\frac{I^*}{I^*+1}$.

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where: $\widetilde{p}_{mt} \equiv (p_{mt} - \alpha_{mt} - \gamma_{mt})/\beta$; $\widetilde{\delta}(n) \equiv \delta(n)/\beta$; and $I^*_{mt} \equiv \sum_{j=1}^{I_t} \frac{1}{1+\widetilde{\delta}(n_{jmt})}$ that can be interpreted as the *effective* number of banks in the local market. The equilibrium value of variable profits is:

$$\pi^*_{imt} = \frac{\beta}{2}\left(\frac{\widetilde{p}_{mt}}{I^*_{mt}+1}\right)^2 \frac{2+\widetilde{\delta}(n_{imt})}{[1+\widetilde{\delta}(n_{imt})]^2}. \tag{9}$$

The value of the parameter $\widetilde{\delta}(n)$ determines the sensitivity of deposits and profits with respect to the number of branches. When this parameter is zero, all the banks active in the market have the same market share, regardless of their number of branches, that is, in a market with $\widetilde{\delta}(n) = 0$, having more than one branch is a waste of resources. When $\widetilde{\delta}(n)$ is strictly positive and declines with n, the market share and the variable profit of a bank increase with the number of own branches and decrease with the number of competing banks and with the number of branches of the competitors.

□ **Estimation of the model of local market competition.** The logarithmic transformation of the equilibrium equation for the amount of deposits, in equation (8), implies that $\ln(D_{imt}) = \ln(\widetilde{p}_{mt}) - \ln(I^*_{mt} + 1) - \ln(1 + \widetilde{\delta}(n_{imt}))$. Based on this expression, we consider the following regression model for the logarithm of deposits: $\ln(D_{imt}) = \alpha_0 + \alpha_1 \ln(D_{imt-1}) + X_{mt}\alpha - \ln(1 + \widetilde{\delta}(n_{imt})) + e_{imt}$, where X_{mt} is a vector of exogenous market characteristics, and e_{imt} is an error term that is unobservable to us as researchers. We are interested in the estimation of the parameters α and the function $\widetilde{\delta}(n)$. We consider a nonparametric specification of this function. To facilitate the interpretation of the estimation results, it is convenient to represent this regression model, and in particular the function $\widetilde{\delta}(n)$, in terms of semi-elasticities. For any value of $n \geq 2$, let $\sigma(n)$ be a function that represents the percentage change in a bank's deposits when the number of branches goes from $n-1$ to n. By definition, there is the following relationship between σ and $\widetilde{\delta}$: $\sigma(n) = -\ln(1 + \widetilde{\delta}(n)) + \ln(1 + \widetilde{\delta}(n-1))$. Therefore, we can represent the regression model for deposits as follows:

$$\ln(D_{imt}) = \alpha^*_0 + \alpha_1 \ln(D_{imt-1}) + X_{mt}\alpha + \sum_{j=2}^{n_{\max}} 1\{n_{imt} \geq j\}\,\sigma(j) + e_{imt}, \tag{10}$$

where the new constant term is $\alpha^*_0 \equiv \alpha_0 - \ln(1 + \widetilde{\delta}(1))$, $1\{.\}$ is the indicator function, and $n_{\max}$ is the maximum number of stores observed in the sample. Based on this expression, we estimate a linear regression model with explanatory variables X_{mt}, $1\{n_{imt} \geq 2\}, \ldots, 1\{n_{imt} \geq n_{\max}\}$ and slope parameters α, $\sigma(2), \ldots, \sigma(n_{\max})$. More precisely, we impose the restriction that $\sigma(n)$ is constant for $n \geq 20$.[28]

It seems reasonable to believe that the error term e_{imt} is partially observable to the bank when it decides the number of branches n_{imt}. Therefore, the dummy variables $1\{n_{imt} \geq j\}$ are endogenous regressors. We assume that e_{imt} has the following *components-of-variance* structure, $e_{imt} = e^{(1)}_{im} + e^{(2)}_{t} + e^{(3)}_{imt}$, where each of these error components can be correlated with the endogenous regressors $1\{n_{imt} \geq j\}$. Under the assumption that $e^{(3)}_{imt}$ is not serially correlated, we have valid instruments in the equation in first differences. In particular, the number of branches and the amount of deposits at periods $t-2$ and before are not correlated with the error term in first differences, $\Delta e^{(3)}_{imt} \equiv e^{(3)}_{imt} - e^{(3)}_{im,t-1}$, and they are correlated with the endogenous regressor because there are adjustment costs and other sources of persistence in the number of branches. The assumption of no serial correlation in $e^{(3)}_{imt}$ can be tested by looking at the second-order serial correlation in

[28] Note that the inability to identify parameter $\sigma(1)$ does not have any relevance for our estimation of deposits and variable profits at any hypothetical value of n. We impose the normalization $\delta(1) = 0$, and construct our estimates of $\widetilde{\delta}(n)$ using the recursive formula $\widetilde{\delta}(n) = [\frac{1+\widetilde{\delta}(n-1)}{\exp\{\sigma(n)\}}] - 1$ for any $n \geq 2$. This normalization is innocuous for the empirical results in this article.

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TABLE 8 Relationship between Number of Branches and Deposits for a Bank in a County

Dependent Variable: $\ln(D_{imt})$		
	Fixed-Effects Estimator[(a,b)]	Arellano-Bond GMM Estimator[(a,b,c)]
Parameter (or explanatory variable)	*Estimate (SE)*	*Estimate (SE)*
$\sigma(2)$	0.2380 (0.0060)***	0.2230 (0.0188)***
$\sigma(3)$	0.1628 (0.0050)***	0.2143 (0.0166)***
$\sigma(4)$	0.1389 (0.1886)***	0.1563 (0.0155)***
$\sigma(5)$	0.1093 (0.0054)***	0.1486 (0.0144)***
$\sigma(6)$	0.0947 (0.0058)***	0.1055 (0.0149)***
$\sigma(7)$	0.0862 (0.0066)***	0.1048 (0.0174)***
$\sigma(8)$	0.0861 (0.0074)***	0.0655 (0.0165)***
$\sigma(9)$	0.0780 (0.0083)***	0.0793 (0.0205)***
$\sigma(10)$	0.0748 (0.0097)***	0.0795 (0.0187)***
$\sigma(11)$	0.0688 (0.0118)***	0.0693 (0.0194)***
$\sigma(12)$	0.0472 (0.0142)***	0.0681 (0.0287)**
$\sigma(13)$	0.0491 (0.0126)***	0.0512 (0.0340)
$\sigma(14)$	0.0300 (0.0138)**	0.0267 (0.0276)
$\sigma(15)$	0.0486 (0.0141)***	0.0708 (0.0277)**
$\sigma(16)$	0.0522 (0.0148)***	0.0307 (0.0286)
$\sigma(17)$	0.0573 (0.0166)***	0.0733 (0.0306)**
$\sigma(18)$	0.0312 (0.0169)*	0.0253 (0.0369)
$\sigma(19)$	0.0622 (0.0170)***	0.0521 (0.0386)
$\sigma(20)$	0.0789 (0.0187)***	0.0292 (0.0320)
$\sigma(n > 20)$	0.0120 (0.0016)***	0.0227 (0.0025)***
ln(Deposits[t-1])	0.4035 (0.0071) ***	0.3475 (0.0078)***
ln(County population)	0.4661 (0.0246)***	0.4116 (0.0428)***
ln(County income per capita)	0.1942 (0.0174)***	0.1247 (0.0142)***
Time dummies (#)	Yes (11)	Yes (10)
County × Bank fixed effects (in levels)	Yes	Yes
Number of observations	277,408	232,812
Test of second-order correlation (p-value)	–	−0.325 (0.745)
Hansen-Sargan test OIR [d.o.f.] (p-value)	–	846 [777] (0.0429)

Note (a): Standard errors robust of heteroskedasticity and serial correlation (clustered over county-bank).
Note (b): $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.
Note (c): Two-step GMM estimator. Equation in first differences. Set of instruments includes lagged endogenous variables from lag *t*-2 to lag *t*-5.

the residuals for $\Delta e_{imt}^{(3)}$. We estimate this model using the Arellano-Bond GMM estimator that is based on the sample moment conditions $\sum_{i,m} Z_{imt}\ \Delta e_{imt}^{(3)} = 0$ from $t = 1996$ until $t = 2006$, where the vector of instruments Z_{imt} consists of the lagged endogenous variables $\{\ln(D_{ims}), 1\{n_{ims} \geq j\} : s = t-2, \ldots, t-5\}$ and the vector of exogenous regressors ΔX_{mt}.

Table 8 presents estimates of the parameters of the model using a fixed-effects method using county-bank fixed effects, and Arellano-Bond GMM in first differences. The two methods provide similar estimates.[29] The test of second-order serial correlation in the residuals $\Delta e_{imt}^{(3)}$ cannot reject the null hypothesis of no correlation, and therefore it supports the validity of lagged endogenous variables as instruments in the GMM estimation. The Hansen-Sargan test of overidentifying restrictions has a p-value of 0.0429, which does not represent a clear rejection of these restrictions.

[29] The similarity of the parameter estimates under the two methods could be explained by the fact that the number of time periods in our panel data set is relatively large. In dynamic panel data models, the fixed-effects estimator is inconsistent when the number of time periods T is fixed, but the bias of this estimator declines monotonically with T and it goes to zero as T goes to infinity.

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The parameter estimates show that the volume of deposits of a bank increases by 22% when the number of branches goes from one to two. This semi-elasticity declines slowly with the number of branches and becomes 14.8% when going from 4 to 5 branches, 7.9% from 9 to 10 branches, and 2.2% for more than 20 branches. The estimated pattern of the semi-elasticity function $\sigma(n)$ clearly rejects restricted versions such as a model with a constant semi-elasticity (i.e., $\sigma(n) = \sigma$, that implies $\delta(n) = \delta$ for any n), or a model with a constant elasticity (i.e., $\sigma(n) = \sigma/n$). The estimated function $\sigma(n)$ implies that the variable cost parameters $\delta(n)$ decline with the number of branches n. According to the model and the estimated parameters, the existence of multiple branches of the same bank in a local market can be explained by the reduction in variable costs, and by competition and strategic complementarity with other banks' branch choices.

□ **Branch networks and geographic risk.** The second component of our model deals with banks' choice of branch network. Every period t, a bank chooses its branch network $\mathbf{n}_{it}$ to maximize its expected value. When the bank chooses its branch network at period t, it has uncertainty about some of the exogenous variables that determine deposits and loans in local markets. Let $\mathbf{X}_t$ be a vector of variables with all the information available to banks at period t. A bank chooses its branch network $\mathbf{n}_{it}$ to maximize its expected value, $\mathbb{E}(V_{it}|\mathbf{X}_t)$.

The existence of adjustment costs (e.g., merging costs, entry costs associated with the start-up of new branches) implies that a bank's choice of branch network is a dynamic decision where the bank is forward looking and takes into account the implications of its choice on future profits. However, the estimation of a dynamic model of network choice and mergers where firms are fully rational and forward looking is a very challenging problem due to the huge dimension of the action space and state space. Our static model implicitly assumes that banks have static expectations such that they believe that the current network will remain constant for a long time in the future. This is also the implicit assumption in recent articles on competition between department store chains, such as Jia (2008) and Ellickson, Houghton, and Timmins (2013). In support of our assumption on beliefs, we can say that in our data set, network changes are relatively infrequent (20% of the bank-year observations) and the median duration between two consecutive adjustments is five years. Furthermore, because dynamics in our model come only from network adjustment costs, we expect that the main biases associated with imposing static expectations are in the estimated magnitude of these adjustment costs.

The value function is equal to the present value (i.e., parameter ρ represents the time discount factor that we fix at $\rho = 0.95$) of variable profits net of fixed costs and costs of liquidity shortage, minus current adjustment costs.

$$\begin{aligned}\mathbb{E}(V_{it}|\mathbf{X}_t) = -AC_{it}(\mathbf{n}_{it}, \mathbf{n}_{it-1}) + \frac{1}{1-\rho}\,[VP_{it}(\mathbf{n}_{it}) - FC_{it}(\mathbf{n}_{it}) \\ -\lambda_{it}\ \Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t)]\,. \end{aligned} \tag{11}$$

(a) A bank's variable profit is the sum of variable profits from all the local markets where the bank is active, $VP_{it}(\mathbf{n}_{it}) \equiv \sum_{m=1}^{M} \pi^*_{imt}$. Given our estimation of the deposit equation (10), we can construct estimates of $VP_{it}(\mathbf{n}_i)$ for any hypothetical value of the number of own stores $\mathbf{n}_i$. In the construction of the variable profits of bank i under hypothetical values of its own network of stores $\mathbf{n}_i$, we impose the Nash assumption and keep the number of stores of the other banks at their observed values. In the Appendix, we describe in detail the construction of these "counterfactual" variable profits using the estimated regression model in equation (10).

(b) Fixed operating costs. The term $FC_{it}(\mathbf{n}_{it})$ consists of the fixed cost of operating the branch network $\mathbf{n}_{it}$. It captures economies of scale and density in the operation of a branch network. It depends on the total number of branches in the network, and on the average distance between these branches. We consider a quadratic specification in terms of the number of branches, that is,

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θ_1^{FC} [#branches] $+\theta_2^{FC}$ [#branches]^2, and of the average distance to the bank's headquarters, that is, θ_3^{FC} [#branches * distance-to-HQs] $+\theta_4^{FC}$ [#branches * (distance-to-HQs)^2].

(c) Adjustment costs. The component $AC_{it}(\mathbf{n}_{it}, \mathbf{n}_{it-1})$ includes costs of adjusting or changing the branch network, including merging costs and costs of *de novo* branching. It depends on the change in total number of branches of the bank, on the form of expansion (through merger or *de novo* branching), and on whether the expansion is within or outside the headquarters state of the bank, that is, θ_1^{AC} [# new branches via *de novo*, within HQs state] $+ \theta_2^{AC}$ [# new branches via *de novo*, outside HQs state] $+ \theta_3^{AC}$ [# new branches via merger, within HQs state] $+ \theta_4^{AC}$ [# new branches via merger, outside HQs state].

We have estimated specifications of the model where adjustment costs are quadratic in the number of branches. However, these specifications suffered from serious collinearity problems and the estimated parameters for the linear and the quadratic terms were quite imprecise. The reason for this collinearity is that conditional on the type of expansion (i.e., *de novo*-within-state, *de novo*-out-of-state, merger-within-state, and merger-out-of-state) there is little sample variation in the time-change for the number of branches, especially for *de novo* expansions. Instead of allowing for quadratic adjustment costs, but aggregating all the forms of geographic expansion in a single form, we have preferred to specify a linear function and to take into account the differences in costs between alternative forms of bank expansion.

(d) Cost of liquidity shortage. The fourth term in a bank's profit, λ_{it} $\Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t)$, is the expected *cost of liquidity shortage*, as described in the Appendix. The term $\Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t)$ is the probability of liquidity shortage, where D_{it} is the total volume of deposits of bank i, L_i represents the bank's illiquid assets (loans), and E_i is the bank's equity. The term λ_{it} represents the cost of liquidity shortage conditional on the existence of that shortage. The following two paragraphs describe and motivate our specification of the probability and the cost of liquidity shortage, respectively.

Suppose that the stochastic process of D_{it} conditional on $\mathbf{X}_t$ is normally distributed, such that the probability of liquidity shortage $\Phi_{it} \equiv \Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t)$ is equal to $\Phi([L_i - E_i - \mathbb{E}(D_{it}|\mathbf{X}_t)]/\sqrt{\mathbb{V}(D_{it}|\mathbf{X}_t)})$, where $\Phi(.)$ is the CDF of the standard normal. To obtain the probability of liquidity shortage, we need to know the bank's volume of loans and equity, L_i and E_i. Here, we are particularly interested in the sample variation of Φ_{it}, over banks and over time, that comes from changes in geographic risk, more than in the sample variation that comes from bank differences in L_i or E_i. Therefore, we fix $L_i - E_i$ such that all the banks have the same Loans-to-Deposit ratio ($LTD \equiv L_i/D_i$) and Equity-to-Deposit ratio ($ETD \equiv E_i/D_i$). Using data from banks' Call Reports during our sample period 1995–2006, we find an average Loans-to-Deposit ratio of 89%, and an average Equity-to-Deposit ratio of 14%.[30] Therefore, the probability of liquidity shortage is $\Phi_{it} = \Phi(\frac{-\tau\ \mathbb{E}(D_{it}|\mathbf{X}_t)}{\sqrt{\mathbb{V}(D_{it}|\mathbf{X}_t)}})$, with $\tau \equiv 1 + ETD - LTD = 0.25$. Note that an increase in the coefficient of variation of deposits, $\sqrt{\mathbb{V}(D_{it}|\mathbf{X}_t)}/E(D_{it}|X_t)$, implies an increase in the probability of liquidity shortage. For instance, if the coefficient of variation goes from 0.10 to 0.15, then the probability of liquidity shortage moves from a negligible 0.6% (i.e., $\Phi(-0.25/0.10)$) to a very substantial 4.8% (i.e., $\Phi(-0.25/0.15)$).

Given that a liquidity shortage occurs, its cost depends on the amount of the shortage and on the cost to cover it by using the interbank money market or by selling illiquid assets (loans) to

[30] The values that we use for the average Loans-to-Deposit ratio (LTD) and the Equity-to-Deposit ratio (ETD) come from banks' Call Reports. These reports provide information on banks' balance sheets at the bank level. More specifically, we use data from the FDIC *Quarterly Banking Profile*, that is available online at cdr.ffiec.gov/public/. The FDIC *Quarterly Banking Profile* contains summary statistics calculated by the FDIC using banks' Call Reports. The observed ratios have variation across banks and over time, but we have used the average (over time and across banks) LTD and ETD ratios. Our measure of the cost of liquidity shortage tries to measure the geographic risk of deposits that comes from the branch network of a bank. We want to identify a bank's concern for risk separately from other sources of financial risk. For this reason, we have preferred to include a measure of the probability of liquidity shortage that only depends on coefficient of variation of a bank's deposits and not on other bank financial variables.

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guarantee deposit withdrawals. It seems plausible that the shortage amount is proportional to the volume of deposits of the bank. The cost of selling illiquid assets depends on the profitability of the investments and loans that the bank has. Because the variable profit of a bank depends both on its volume of deposits and on the profitability of its loans, we specify the cost of liquidity shortage as proportional to variable profit: $\lambda_{it} = \overline{\lambda}\ VP_{it}$, where $\overline{\lambda}$ is a parameter that is unknown to the researcher. These specification assumptions imply that the value of a bank network is $E(V_{it}|X_t) = -\ AC_{it} + (1-\rho)^{-1}\ [(1-\overline{\lambda}\ \Phi_{it})\ VP_{it} -\ FC_{it}]$, where Φ_{it} is the probability of liquidity shortage, and the parameter $\overline{\lambda}$ can be interpreted as an *ad valorem* tax, that is, a probability of liquidity shortage Φ_{it} is equivalent to a tax $\overline{\lambda}\ \Phi_{it}$ on variable profits.

For the estimation of this model, it is convenient to represent the expected value of a bank as $E(V_{it} \mid \mathbf{X}_t) = W_{it}(n_{it})\,\theta + \varepsilon_{it}(n_{it})$, where $W_{it}(n_{it})$ is the vector of known functions $\{VP_{it}(n_{it}), -\Phi_{it}\ VP_{it}(n_{it})$, [#branches], [#branches]^2, [#branches * distance-to-HQs], [#branches * (distance-to-HQs)^2], [# new branches via *de novo*, within HQs state], [# new branches via *de novo*, outside HQs state], [# new branches via merger, within HQs state], [# new branches via merger, outside HQs state]$\}$, θ is the vector of parameters $(\frac{1}{1-\rho}, \frac{\overline{\lambda}}{1-\rho}, \frac{\theta_1^{FC}}{1-\rho}, \frac{\theta_2^{FC}}{1-\rho}, \frac{\theta_3^{FC}}{1-\rho}, \frac{\theta_4^{FC}}{1-\rho}, \theta_1^{AC}, \theta_2^{AC}, \theta_3^{AC}, \theta_4^{AC})'$, and $\varepsilon_{it}(n_{it})$ represents other factors that are unobservable to the researcher but known to the bank.

□ **Estimation of the model of branch network.** We apply the principle of revealed preference to estimate (up to scale) the vector of parameters $\boldsymbol{\theta}$. We assume that every year t, bank i chooses its network $\mathbf{n}_{it}$ to maximize its expected value:

$$\mathbf{n}_{it} = \arg\max_{\mathbf{n}\in A_{it}} \{W_{it}(\mathbf{n})\,\boldsymbol{\theta} + \varepsilon_{it}(\mathbf{n})\}, \tag{12}$$

where A_{it} is the set of feasible networks for bank i at year t. We estimate the structural parameters of our model using a *Moment Inequalities estimator* (MIE) (see Pakes, 2010; Pakes et al., 2015). Let $\boldsymbol{\theta}^0$ be the "true" value of the vector of structural parameters. Revealed preference implies that the value of a bank under its actual choice $\mathbf{n}_{it}$ cannot be smaller than the value of that bank for any other feasible choice of network. That is, for any vector $\mathbf{n}$ in the feasible set A_{it}, the following inequality should hold: $W_{it}(\mathbf{n}_{it})\ \boldsymbol{\theta}^0 + \varepsilon_{it}(\mathbf{n}_{it}) \geq W_{it}(\mathbf{n})\ \boldsymbol{\theta}^0 + \varepsilon_{it}(\mathbf{n})$. These inequalities still hold when we integrate the two sides over the distribution of ε_{it} conditional on the observable predetermined state variables $\mathbf{X}_t$:

$$\mathbb{E}\left(\ W_{it}(\mathbf{n}_{it})\frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} + \frac{\varepsilon_{it}(\mathbf{n}_{it})}{\sigma_\varepsilon} - W_{it}(\mathbf{n})\frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} - \frac{\varepsilon_{it}(\mathbf{n})}{\sigma_\varepsilon} \mid \mathbf{X}_t\right) \geq 0, \tag{13}$$

where σ_ε is the standard deviation of the unobservables $\varepsilon_{it}(\mathbf{n})$. By assumption, $\varepsilon_{it}(\mathbf{n})$ is independent of $\mathbf{X}_t$ and has zero mean such that $\mathbb{E}(\varepsilon_{it}(\mathbf{n}) \mid \mathbf{X}_t) = 0$. However, the value of $\varepsilon_{it}(\mathbf{n}_{it})$ associated with the actual/optimal choice $\mathbf{n}_{it}$ is not independent of $\mathbf{X}_t$ because of the endogenous selection of $\mathbf{n}_{it}$. The selection term $\mathbb{E}(\varepsilon_{it}(\mathbf{n}_{it}) \mid \mathbf{X}_t)$ has a complex form because the unobservables $\{\varepsilon_{it}(\mathbf{n}) : \mathbf{n} \in A_{it}\}$ have potentially a complicated correlation structure across the different possible network choices. To deal with this selection problem, we impose a restriction on the support of the unobservables $\varepsilon_{it}(\mathbf{n})$. We assume that the support of the distribution of the standardized variables $\varepsilon_{it}(\mathbf{n})/\sigma_\varepsilon$ has a finite upper bound such that $\varepsilon_{it}(\mathbf{n})/\sigma_\varepsilon \leq K < \infty$, that is, the unobservables can take values at most K times the standard deviation. Under this restriction, it is clear that the selection term is $\mathbb{E}(\varepsilon_{it}(\mathbf{n}_{it}) \mid \mathbf{X}_t) \leq K$. Therefore, we can write the following system of unconditional moment inequalities that includes only observable variables and unknown parameters:

$$\mathbb{E}\left(\mathbf{Z}_{it}\ \left[(W_{it}(\mathbf{n}_{it}) - W_{it}(\mathbf{n}))\frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} + K\right]\right) \geq 0, \tag{14}$$

where $\mathbf{Z}_{it} = \{\mathbf{Z}_{hit} : h = 1, 2, \ldots, H\}$ is a vector of instruments, that is, known functions of predetermined state variables $\mathbf{X}_t$ and of exogenous bank characteristics. The most attractive feature of this estimation method is that its consistency does not rest on any particular parametric

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assumption about the distribution of the $\varepsilon's$ or on restrictions imposed on the correlation structure of these unobservables across possible network choices.

Following Chernozukov, Hong, and Tamer (2007), for the estimation of $\boldsymbol{\theta}^0/\sigma_\varepsilon$ we choose a value that minimizes a sample criterion function that penalizes the violation of these inequalities. Because the total number of inequalities that we may consider is extremely large (i.e., equal to the number of all possible branch networks in the set A_{it}), we consider only values of branch networks $\mathbf{n}$ in a subset C_{it} within the set of feasible networks A_{it}. We describe below the subsets C_{it}. The estimator of $\widetilde{\boldsymbol{\theta}}^0 \equiv \boldsymbol{\theta}^0/\sigma_\varepsilon$ is defined as:

$$\widehat{\boldsymbol{\theta}}_{MIE} = \arg\min_{\widetilde{\theta}} \sum_{h,\mathbf{n}\in C_{it}} \left[\max\left\{ -\sum_{i=1}^{I_t}\sum_{t=1}^{T} \mathbf{Z}_{hit}\left[\left(W_{it}(\mathbf{n}_{it}) - W_{it}(\mathbf{n})\right)\widetilde{\theta} + K \right] \; ; \; 0 \right\} \right]^2 . \tag{15}$$

Note that the constant K is not identified and we should fix its value. There is a trade-off in the choice of K. The greater K, the less efficient is our estimator. However, if we fix K at a value that is smaller than its unknown true value, our estimator is inconsistent and the bias increases with the distance between the true K and our choice of this parameter. Ideally, we would like to choose K large enough such that we avoid potential biases but not too large such that we still have precise estimates. Given the large number of observations and the very large number of possible choice alternatives in our application, we have been able to get precise and robust estimates for relatively large values of K such as $K \in [4, 6]$, that is, the upper bound in the support of the unobservables can be up to six times the standard deviation.[31]

The selection of the sets of choice alternatives C_{it} is important for a precise estimation (and for the point identification) of all the parameters. The selection of these sets should imply enough variation with respect to $\mathbf{n}$ for every component of the vector $W_{it}(\mathbf{n}_{it}) - W_{it}(\mathbf{n})$. At the same time, for computational reasons, the number of elements in C_{it} should be orders of magnitude smaller than the number of elements in A_{it}. For every bank-year observation (i, t) in our sample, the set C_{it} contains the actual choice, n_{it}, and the following hypothetical networks of branches: (a1) opening (closing) up to five branches in the bank's headquarters-county (HQs); (a2) same as (a1) but in the county closest to HQs; (a3) same as (a1) but in the county with the highest expected log-deposits-per-branch within the HQs state; (a4) same as (a1) but in the county with the lowest risk within the HQs state; (a5) same as (a1) but in the county with the lowest correlation within the HQs state; (b3)-(b4)-(b5) same as (a3)-(a4)-(a5) but for counties in states that share a border with the HQs state; (c3)-(c4)-(c5) same as (a3)-(a4)-(a5) but for counties in states that do not share a border with the HQs state; (d1) merger with the largest, or second largest, or third largest bank (in terms of number of branches) in HQs; (d2) same as (d1) but in the county closest to HQs; (d3) same as (d1) but in the county with the highest expected log-deposits-per-branch within the HQs state; (d4) same as (d1) but in the county with the lowest risk within the HQs state; (d5) same as (d1) but in the county with the lowest correlation within the HQs state; (e3)-(e4)-(e5) same as (d3)-(d4)-(d5) but for counties in states that share a border with the HQs state; and (f3)-(f4)-(f5) same as (d3)-(d4)-(d5) but for counties in states that do not share a border with the HQs state.

[31] Aguirregabiria, Luo, and Yuan (2015) study this estimation method in the context of a general class of discrete-choice Random Utility Models that includes the discrete game in this application. They provide sufficient conditions for point identification of structural parameters using this method, propose a cross-validation method for the choice of the incidental parameter K, and present Monte Carlo experiments. In all their Monte Carlo experiments, the Mean Square Error (MSE) of the parameters (i.e., the cross-validation function) is a convex function of the parameter K. More specifically, the absolute bias of the estimator declines with K (when K is relatively small) and the variance of the estimator increases monotonically with K. For low values of K, an increase in this parameter has a stronger bias-reduction-effect than variance-increase-effect, such that the MSE declines. For high values of K, (i.e., values of K greater than its true value) an increase in this parameter does not have any effect on the bias, but it increases the variance and the MSE. Given the large magnitude of the estimation problem in this application, in terms of both sample size and number of parameters, the implementation of a cross-validation method for the choice of the parameter K is computationally very costly. However, our approach to choose the value of K (see below) has some similarities with a cross-validation approach.

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TABLE 9 Estimation of Bank Network Costs and Benefits Based on Moment Inequalities: Years 1995–2006

Parameter	Estimate[(a)]	(SE)[(a)]
$1/\sigma_\varepsilon$	3.2135***	(0.8720)
Cost of liquidity shortage parameter $\overline{\lambda}$ (%)	8.4380***	(1.5200)
Branch-network diseconomies of scale:		
Number of branches (in million $ per branch)	−1.9802***	(0.6163)
Number of branches square (in million $ per branch sq.)	−0.0706	(0.0620)
Branch-network economies of density:		
Average distance to county HQs (in million $ per 100 miles and per branch)	−0.1435***	(0.0387)
Average distance to county HQs square	0.0050	(0.0063)
Branch-network adjustment costs. De novo branching:		
De novo branch creation within-state (in million $ per branch)	−1.3325**	(0.2803)
De novo branch creation out-of-state (in million $ per branch)	−2.1597**	(0.4239)
Branch-network adjustment costs. Merger:		
Merger within-state (in million $ per new branch)	−0.6480*	(0.3985)
Merger out-of-state (in million $ per new branch)	−1.1871**	(0.4200)
Merger within-state × small bank dummy (in million $ per new branch)	−1.4410*	(0.9106)
Merger out-of-state × small bank dummy (in million $ per new branch)	−2.4309***	(0.6767)
Number of observations (#banks)	120,812 (14,127)	

Note (a): Bootstrap standard errors resampling banks and using 500 bootstrap samples with 14,127 banks each. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Each subset C_{it} contains a maximum of 196 choice alternatives, but in most of the cases the number of choice alternatives is around 100.

Our measure of bank geographic risk, based on the estimated factor model, plays a key role in this identification. This risk measure has substantial sample variation across banks after controlling for the number of branches (i.e., economies of scale), and for the geographic distance between these branches (i.e., economies of density). This is because banks' networks have home counties or regions with different levels of risk, as estimated in the factor model. The main intuition behind the identification of our estimates is the following. We observe that most banks expand their networks around their home county, and we find that this pattern is explained by economies of density. We also observe that banks located in home counties with higher levels of risk, and/or surrounded by counties with relatively lower risk, have a greater propensity to expand geographically. We find that this evidence is explained by banks' concern with reducing geographic risk.

Table 9 presents our estimates of bank preferences when we fix $K = 5$. The estimation results are very similar for other values of K between 4 and 6, they are significantly different for $K < 4$, and the estimates become imprecise for $K > 6$. Standard errors are constructed using the bootstrap method, where we resample the whole history of a bank. The estimate of parameter $\overline{\lambda}$ that measures banks' concerns for deposit risk is statistically and economically significant. Each percentage point of probability of liquidity shortage is equivalent to an *ad valorem* tax on deposits of 8.4%. The estimates of the parameters related to fixed operating cost show significant diseconomies of scale and economies of density. The fixed cost of the first branch is $1.98 million, and the cost per branch increases with the number of branches. The cost per branch of a network with 10 branches is $2.68 million. We also find evidence of significant economies of density. The operating cost increases with the average distance of the branch network to the county with the bank's headquarters. Every 100 miles of average distance to the headquarters implies an increase in the cost-per-branch of $143,000. According to these estimates, for a branch network with 10 branches, the total fixed cost is $28.2 million if the average distance is 100 miles, and this cost increases to $34.4 million if the average distance is 500 miles.[32]

[32] Using data of banks in Italy, Felici and Pagnini (2008) also obtain evidence of economies of density in bank branching and find that larger banks are more able to cope with distance-related entry costs than small banks.

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The estimated costs of *de novo* branching and merging are sizeable. There are significant differences in these costs if the expansion is within the same state or to another state. The cost of a new branch is \$1.3 million within the state, and it increases to \$2.1 million if the new branch is opened in a state different from the bank headquarters. The estimated merging cost per acquired branch is smaller than the cost of *de novo* branching, especially for out-of-state expansions. We also find that merging costs per acquired branch are larger for small banks, defined as banks with three branches or less.

□ **Counterfactual experiments.** Based on these estimates of the model, we implement several counterfactual experiments to illustrate the contributions of GRD, economies of density, and adjustment costs to the geographic expansion of US banks, and to evaluate the effects of RN on banks' geographic risk. We focus on the following outcome variables at the bank level: (i) the indicator that the bank has at least one branch outside its home county; (ii) the indicator that the bank has at least one branch outside its home state; and (iii) the bank's geographic deposit risk. All these outcome variables are for the last year in the sample, that is, year 2006.

Let Y_i represent one of the outcome variables mentioned above. Given the model for a bank's optimal choice of network, as described in equation (12), this outcome variable is a function of the initial networks at year 1994 ($\mathbf{n}_{94}$), the sequence of realizations of the observable exogenous variables between 1994 and 2006 ($\mathbf{X}$), the sequence of realizations of unobservable variables (ε), the sequence of feasible choice sets ($\mathbf{A}$), and the vector of structural parameters ($\boldsymbol{\theta}$). We can represent this relationship in a compact form using the expression $Y_i = y_i(\mathbf{n}_{94}, \mathbf{X}, \varepsilon, \mathbf{A}, \boldsymbol{\theta})$, where $y_i()$ is the function that results from the sequential application of equation (12) between years 1994 and 2006 and the definition of the outcome variable as a function of the bank's network at year 2006. Let $\widehat{\boldsymbol{\theta}}$ be the vector with our estimates of the structural parameters. In addition, let $\boldsymbol{\theta}^*$ be the vector with the counterfactual values of these parameters. For instance, in counterfactual experiment 1, the vector $\boldsymbol{\theta}^*$ is the same as the estimated vector $\widehat{\boldsymbol{\theta}}$ except that the parameter $\overline{\lambda}$ that represents banks' concern for geographic risk is equal to zero. We are interested in obtaining the treatment effects:

$$TE_i = y_i(\mathbf{n}_{94}, \mathbf{X}, \varepsilon, \mathbf{A}, \boldsymbol{\theta}^*) - y_i(\mathbf{n}_{94}, \mathbf{X}, \varepsilon, \mathbf{A}, \widehat{\boldsymbol{\theta}}). \tag{16}$$

This treatment effect represents the change in the outcome variable for bank i if we keep the sequence of all the exogenous variables constant but we change the structural parameters from $\widehat{\boldsymbol{\theta}}$ to $\boldsymbol{\theta}^*$. This is the causal effect on the outcome variable of changing structural parameters from $\widehat{\boldsymbol{\theta}}$ to $\boldsymbol{\theta}^*$.

Unfortunately, we cannot obtain these causal effects. First, the extremely large dimension of the choice sets A_{it} makes it intractable to solve exactly the optimization problem in equation (12). Second, as it is common in discrete-choice models, we cannot get estimates of the unobservables ε as residuals from the estimated model. To deal with the first problem, we replace the feasible sets A_{it} with the consideration sets C_{it} that we have used for the construction of moment inequalities at the estimation stage. Each of these consideration sets contains a maximum of only 196 choice alternatives, and therefore they are very manageable. To deal with the unobservables ε, we calculate average treatment effects by integrating over the sequence of ε's, that is, $ATE_i = \mathbb{E}_\varepsilon[y_i(\mathbf{n}_{94}, \mathbf{X}, \varepsilon, \mathbf{A}, \boldsymbol{\theta}^*) - y_i(\mathbf{n}_{94}, \mathbf{X}, \varepsilon, \mathbf{A}, \widehat{\boldsymbol{\theta}})]$. For this integration, we have considered that the unobservables have a type 1 extreme value distribution that is i.i.d. over time, banks, and choice alternatives. Of course, this is a strong assumption. Our interpretation of this approach is not really as an assumption on the distribution of the unobservables but as a kernel function that we use to smooth treatment effects that otherwise would be very nonsmooth functions of $(\mathbf{n}_{94}, \mathbf{X}, \theta^*)$. Therefore, it is more accurate to describe these statistics as *integrated treatment effects* instead

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TABLE 10 Counterfactuals: Risk Concern, Economies of Density, Adjustment Costs

Statistic	Actual Value	Model Prediction	Avg. Counterf. Outcome Exp. 1 $\overline{\lambda}=0$	Exp. 2 $\theta_3^{FC}, \theta_4^{FC}=0$	Exp. 3 $\theta^{AC}=0$
Small banks (one branch @ first year)					
Branching outside home county in 2006 (%)	28.7	**30.1**	13.9	37.4	67.0
Branching outside home state in 2006 (%)	2.8	**3.2**	0.2	4.6	15.9
Geographic deposit risk in 2006 (percentage points)	2.75	**2.71**	2.97	2.59	2.21
Medium banks (2–10 branches @ first year)					
Branching outside home county in 2006 (%)	64.9	**62.6**	58.6	70.1	78.9
Branching outside home state in 2006 (%)	8.3	**7.9**	7.5	20.7	22.4
Geographic deposit risk in 2006 (percentage points)	2.20	**2.26**	2.36	2.19	2.08
Large banks (>10 branches @ first year)					
Branching outside home county in 2006 (%)	96.7	**93.8**	93.6	98.9	99.0
Branching outside home state in 2006 (%)	40.0	**37.3**	37.3	43.5	60.1
Geographic deposit risk in 2006 (percentage points)	1.91	**1.95**	1.95	1.91	1.90

of average treatment effects.[33] We calculate these treatment effects for the 8713 banks that are active at year 2006.

Table 10 presents results from three experiments. We report treatment effects ATE_i averaged across banks for three different groups according to their size at their initial year in the sample: small banks (i.e., one branch), medium (2 to 10 branches), and large banks (more than 10 branches).[34] In Experiment 1, we shut down the effect of GRD by making the parameter $\overline{\lambda}$ equal to zero. We find that eliminating banks' concern for risk has a very important impact on the network expansion of small banks but a negligible effect on medium and large banks. For small banks, the probability of having a branch outside the home county declines from 30.1% to 13.9%, and the probability of expanding out of the home state becomes practically zero. As a result, deposit risk of these small banks increases from 2.71 to 2.97 percentage points. Therefore, banks' concern for GRD is an important factor to explain the observed patterns of expansion of small banks in the data. In Experiment 2, we eliminate economies of density by fixing θ_3^{FC} and θ_4^{FC} to zero. We find that shutting down economies of density has an important effect on the network expansion of all the banks, though the stronger effect is for banks of medium size. All the banks increase their probabilities of network expansion within and outside the home state. The larger increase is for the out-of-state expansion of medium banks. This effect is more modest for small banks because they have larger adjustment costs. Eliminating economies of density implies a substantial reduction in geographic risk. In Experiment 3, we shut down adjustment costs, both for *de novo* branching and for mergers. The effects of this counterfactual are also

[33] An alternative approach to deal with the unobservable ε's consists of obtaining treatment effects evaluated at the mean value of the sequence of ε's (at $\varepsilon = \mathbf{0}$), that is, $TE_i(\varepsilon = \mathbf{0}) = y_i(\mathbf{n}_{94}, \mathbf{X}, \mathbf{0}, \mathbf{A}, \boldsymbol{\theta}^*) - y_i(\mathbf{n}_{94}, \mathbf{X}, \mathbf{0}, \mathbf{A}, \widehat{\boldsymbol{\theta}})$. A main advantage of this approach is that it does not require any information on the stochastic process of the unobservables (over time, banks, or counties) such that it maintains this robustness feature of our estimation method. However, this approach has some limitations. First, $TE_i(\varepsilon = \mathbf{0})$ does not have an interpretation as an average or median treatment effect. Most importantly, $TE_i(\varepsilon = \mathbf{0})$ is a very nonsmooth function of the $(\mathbf{n}_{94}, \mathbf{X}, \boldsymbol{\theta}^*)$. For instance, it is equal to zero for many banks, and very small changes in $\boldsymbol{\theta}^*$ or in the initial network of a bank can imply a substantial jump in the value of $TE_i(\varepsilon = \mathbf{0})$. This nonsmoothness is not an attractive property for a summary statistic. Although this problem is reduced when the treatment effects $TE_i(\varepsilon = \mathbf{0})$ are averaged across many banks, it is still an important issue when these averages are over a small number of banks, such as banks from a single state or in a particular size group. The integrated treatment effect approach, that we use in this article, deals with this issue. As a test of robustness of the integrated approach, we have implemented the two methods to calculate treatment effects averaged over all the banks, and we have found very similar results.

[34] In the sample of 8753 banks active in 2006, there are 4750 banks (54.5%) with a single branch at the initial year, 3653 banks (41.9%) with 2 to 10 branches, and 310 banks (3.5%) with more than 10 branches.

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TABLE 11 Counterfactuals: The Effects of Riegle-Neal

Statistic[a]	(1) With RN and with ACs	(2) Without RN and with ACs	(3) With RN and without ACs	(4) Without RN and without ACs
Small banks in small states (195 banks)				
Branching outside home county in 2006 (%)	14.9	16.3	41.7	51.7
Branching outside home state in 2006 (%)	6.6	0.0	29.9	0.0
Geographic deposit risk in 2006 (% points)	2.85	2.98	2.36	2.72
Medium banks in small states (252 banks)				
Branching outside home county in 2006 (%)	49.2	49.9	58.6	62.5
Branching outside home state in 2006 (%)	14.3	0.0	32.4	0.0
Geographic deposit risk in 2006 (% points)	2.46	2.70	2.20	2.61
Large banks in small states (35 banks)				
Branching outside home county in 2006 (%)	91.4	91.4	100.0	100.0
Branching outside home state in 2006 (%)	14.3	0.0	80.0	0.0
Geographic deposit risk in 2006 (% points)	2.19	2.35	1.95	2.33
Small banks in medium states (2554 banks)				
Branching outside home county in 2006 (%)	28.2	30.1	58.2	65.9
Branching outside home state in 2006 (%)	2.8	0.0	17.9	0.0
Geographic deposit risk in 2006 (% points)	2.76	2.81	2.29	2.59
Medium banks in medium states (2064 banks)				
Branching outside home county in 2006 (%)	68.7	70.2	77.9	80.1
Branching outside home state in 2006 (%)	9.1	0.0	23.1	0.0
Geographic deposit risk in 2006 (% points)	2.23	2.31	2.03	2.29
Large banks in medium states (231 banks)				
Branching outside home county in 2006 (%)	96.9	97.3	100.0	100.0
Branching outside home state in 2006 (%)	43.3	0.0	59.2	0.0
Geographic deposit risk in 2006 (% points)	2.05	2.26	1.96	2.25
Small banks in large states (2001 banks)				
Branching outside home county in 2006 (%)	30.7	32.0	70.5	90.0
Branching outside home state in 2006 (%)	2.5	0.0	13.2	0.0
Geographic deposit risk in 2006 (% points)	2.74	2.76	2.19	2.22
Medium banks in large states (1337 banks)				
Branching outside home county in 2006 (%)	62.1	65.0	85.2	92.2
Branching outside home state in 2006 (%)	5.9	0.0	30.3	0.0
Geographic deposit risk in 2006 (% points)	2.17	2.19	1.98	2.14
Large banks in large states (44 banks)				
Branching outside home county in 2006 (%)	100.0	100.0	100.0	100.0
Branching outside home state in 2006 (%)	43.2	0.0	86.3	0.0
Geographic deposit risk in 2006 (% points)	1.91	1.92	1.90	1.92

Note (a): Small state = #counties $\leq$16; medium state = #counties between 19 and 92; large state = #counties $\leq$95.

substantial, especially for small banks. Eliminating adjustment costs increases the probability that small banks have branches outside their home county (home state) from 30.1% (3.2%) to 67.0% (15.9%). As a result of this substantial geographic expansion of small banks, their geographic risk would decline by 0.5 percentage points, from 2.71 to 2.21.

Table 11 presents counterfactual experiments that evaluate the effect of RN. We evaluate the effects of RN by considering a counterfactual scenario where banks cannot expand their branch network out of state. We report these effects for nine groups of banks according to their initial size (small, medium, and large banks, with the same definition as in Table 10) and to the size of their headquarter state, as measured by number of counties in the state: small states (with 16 counties or fewer), medium-size states (between 19 and 92 counties), and large states (i.e., more than 94 counties). We consider two different versions of this counterfactual experiment: with and without adjustment costs (AC). Column (1) presents the predictions of the model

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with RN and with adjustment costs, and column (2) presents the counterfactual without RN but keeping adjustment costs. The comparison of these two columns provides an evaluation of the effects of RN during the sample period. Columns (3) and (4) provide a similar exercise but for the scenario without adjustment costs that tries to represent the long-run effects of RN. The effects of RN without adjustment costs are important for banks in all the states, but especially for banks with headquarters in small states. For these banks, the possibility of out-of-state expansion implies a reduction in geographic risk (without adjustment costs) of 0.36 percentage points for small banks, 0.41 points for medium-size banks, and 0.38 points for large banks.

Summarizing, our estimates of bank preferences show that deposit risk has an important negative effect on the value of a bank. However, this concern for risk diversification has been counterbalanced by economies of density and costs of expansion either through *de novo* branching or through mergers.

7. Conclusion

■ Our findings suggest that RN has substantially expanded the possibilities for geographic diversification of deposit risk for banks from small and homogeneous states. However, banks have not taken advantage of these opportunities such that only a small amount of the reduction in geographic risk since 1994 can be attributed to RN. Our estimates of bank preferences show that deposit risk has an important negative effect on the value of a bank, but that this concern for risk has been counterbalanced by concerns over economies of density and merging costs.

The fact that most US banks remained geographically nondiversified more than a decade after the enactment of RN had important ramifications during the financial crisis of 2007–2008. Specifically, during the crisis bank failures were, to a large extent, concentrated in particular geographic locations. For instance, 79 of 440 bank failures between the beginning of 2007 and 2012 occurred in Georgia. One reason for this is that banks in Georgia were, despite the opportunities afforded by RN, by and large quite small, and so their interests remained very local. Because the residential crisis hit Georgia particularly hard, its nondiversified banks suffered.

A clear implication of our analysis is that simply granting banks the right to expand across state lines does not necessarily mean that they will act to lower their overall levels of geographic risk. Because of economies of density and merger costs, some banks are reluctant to expand far away from their headquarters. This is what we find in our estimation in Section 5. Moreover, larger banks, with relatively smaller merging costs, expanded out of their home state but not to reduce their geographic risk, but to increase expected log-deposits-per-branch. Together, these findings suggest that the policy has not achieved its stated objective.

To encourage small banks to diversify in such a way as to lower geographic risk, in addition to allowing across-state expansion, policy makers will have to find ways to reduce merger costs and make expansion more attractive. Some of this will happen naturally as a result of technological improvements. With the rise of Internet banking, the importance of the branch network will diminish, as will the need for branches to be in close proximity to headquarters.

Of course, ever since the financial crisis, policy makers may be less inclined toward the idea of encouraging greater expansion and more concentration in the banking industry. To avoid systemic risk, many have proposed shrinking too-big-to-fail institutions through divestiture.

Appendix

The Appendix contains detailed descriptions of some technical aspects of the paper such as the construction of efficient frontiers and the counterfactual empirical distributions of bank risk and expected returns.

□ **Branch creation through mergers and *de novo* branches.** Let n_{imt} be the number of branches of bank i in county m at year t. Also, let Δn_{imt} be the net change in the number of branches between years $t-1$ and t, that is, $\Delta n_{imt} \equiv n_{imt} - n_{imt-1}$. We can represent this net change as the sum of two components: $\Delta n_{imt} = \Delta n_{imt}^{M} + \Delta n_{imt}^{D}$, where Δn_{imt}^{M} is the net change due to a merger or acquisition, and Δn_{imt}^{D} is the net change due to *de novo* openings or closings of branches. If bank i has not acquired during year t any of the banks with branches in market m at $t-1$, then it is

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clear that the total net change Δn_{imt} should be attributed to *de novo* branching, that is, $\Delta n_{imt} = \Delta n^D_{imt}$. Otherwise, if during year t bank i has acquired other bank(s) with branches in county m, we assume that there has been first a merger and then a decision of opening or closing branches. According to this assumption, Δn^M_{imt} is equal to the total number of branches that the acquired bank (or banks) had in county m at year $t-1$, and Δn^D_{imt} is constructed as the residual change $\Delta n^D_{imt} = \Delta n_{imt} - \Delta n^M_{imt}$.

□ **Relationship between liquidity risk and rate of return on equity.** This section of the Appendix presents a simple model that helps to illustrate the relationship between a bank's liquidity risk and its rate of return on equity (ROE).

A bank at period t has equity E_t, total deposits D_t, total illiquid loans/assets L_t (that cannot be liquid in the short run without implying a large cost), and total liquid assets, B_t. The bank balance sheet implies the identity $E_t + D_t = L_t + B_t$, that is, total liabilities equal total assets. For simplicity, suppose that equity E_t and illiquid assets L_t are constant over time, that is, they represent long-term decisions. The bank has uncertainty about the amount of depositor withdrawals, and therefore there is risk in the volume of deposits D_t. We say that the bank experiences a liquidity shortage if it has to sell part of its illiquid assets L to guarantee deposit withdrawals. In the absence of a liquidity shortage, we have that the amount of liquid assets adjusts to the change in the volume of deposits such that $B_t = B_{t-1} + [D_t - D_{t-1}]$. However, when deposit withdrawals are large enough such that $B_{t-1} + [D_t - D_{t-1}] < 0$, the bank should sell some of its illiquid assets. Therefore, we can represent a liquidity shortage in terms of the condition $B_{t-1} + [D_t - D_{t-1}] < 0$. Taking into account the balance sheet identity at period $t-1$ (i.e., $E + D_{t-1} = L + B_{t-1}$), the condition for liquidity shortage can be expressed as $D_t < L - E$. Suppose that the stochastic process for the bank deposits is $\ln(D_t) = \mu + \sigma\, u_t$, where μ and σ are parameters that are known with certainty, and u_t is a random variable with zero mean and median, unit variance, and CDF $\Phi(.)$. This stochastic process for bank deposits is a simplification with respect to the factor model presented above, but we can think of the parameter σ as a measure of the deposit risk for the bank. Then, the probability of a liquidity shortage is $p = \Phi(\frac{\ln(L-E)-\mu}{\sigma})$.

This equation shows the relationship between the probability of a liquidity shortage, p, the deposit risk, σ, and the variable $\ln(L-E)$ that is related to the rate of return on equity. If the return to liquid assets and the interest rate for deposits are close to zero, then the rate of return on equity for the bank is equal to $ROE \equiv r(L-E)/E$, where r is the interest rate of loans. Combining this definition with the previous expression for the probability of a liquidity shortage, and given the invertibility of the CDF $\Phi(.)$, we can get the following relationship between ROE, p, and σ: $\ln(ROE) = \alpha + \sigma\ \Phi^{-1}(p)$, where $\alpha \equiv \ln(r) - \ln(E) + \mu$. Given that $\Phi^{-1}(p)$ is an increasing function over [0, 1], we have that there is a positive relationship between ROE and p. The key parameter that determines the strength of this relationship is σ, that is, deposit risk. Using this equation, we can get the partial derivative $\partial \ln(ROE)/\partial\sigma = \Phi^{-1}(p)$, which is negative for $p < 0.5$. The effect of deposit risk on the bank rate of return (keeping p fixed) depends on the level of p and on the distribution function $\Phi(.)$. For distributions close to the normal (i.e., log normal deposits) and probabilities of liquidity shortage smaller than 15%, we have that $\Phi^{-1}(p) < -1$ such that one percentage point reduction in deposit risk implies more than a one percentage point increase in a bank's rate of return on equity.

□ **Efficient risk-expected return frontiers.** The standard (Markovitz) efficient risk-expected return frontier is a real-valued function $f(.)$ that relates the expected return of a portfolio with the risk of the portfolio, that is, $R = f(S)$, such that $f(S)$ is the maximum expected return of a portfolio with risk S. Let w_m be the share of asset m in the portfolio. When all the assets are perfectly divisible and the investor can be short of any asset, we have that the efficient frontier $f(S)$ is the maximum (in $w_1, w_2, \ldots, w_M$) of $\sum_{m=1}^{M} w_m\ \mu^*_m$ subject to $\sum_{m=1}^{M} w_m = 1$, and $\sum_{m=1}^{M}\sum_{m'=1}^{M} w_m w_{m'}\ \sigma^*_{mm'} = S^2$. However, the portfolio choice problem and the efficient frontiers that we consider in this article are not standard. First, in our case, the unit of each asset is a branch that is discrete and indivisible, that is, the weights w_m are not continuous variables. Second, banks cannot be short on branches in any local market such that the weights w_m cannot take negative values. Third, before RN, banks in different states had different sets of assets/markets where they could invest. Finally, we also take into account that most banks have a "home bias" to invest in the local market where they originated and have their headquarters. Our construction of efficient portfolio frontiers takes into account these important aspects that affect the branch portfolio of a bank. Given a set of states G, a "home" local market h, and a maximum number of branches $maxn$, let $A(G, h, maxn)$ represent the set of possible branch-networks (portfolios) that satisfy the following conditions: (i) all the branches are located in counties that belong to states in set G; (ii) there is at least one branch in home county h; and (iii) the total number of branches in the network is lower or equal than $maxn$. Given the feasible set $A(G, h, maxn)$, the efficient frontier is defined as the set of risk-expected return pairs (S, R) such that $R = f(S|G, h, maxn)$ and:

$$f(S|\text{G,h,maxn}) = \max_{\{n_1,n_2,\ldots,n_M\}} \sum_{m=1}^{M} \left(\frac{n_m}{maxn}\right)\ \mu^*_m$$

$$\text{subject to: } n_m = 0 \quad \text{if } m \notin G;\ n_h > 0;\ \sum_{m=1}^{M} n_m \le maxn;$$

$$\text{and } \sum_{m=1}^{M}\sum_{m'=1}^{M}\left(\frac{n_{im}}{maxn}\right)\left(\frac{n_{im'}}{maxn}\right)\sigma^*_{mm'} = S^2. \tag{A1}$$

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TABLE A1 Description of Counterfactual Distributions in Figures 12 and 13

	Bank History 1995–2006					Counterfactual Distribution $f(\Omega_{06}, I_{06}^{IN}, n_{06}^{IN})$		
	ACT	ACTMERG	MERG	MERGOUT	# Banks (%)	Set I_{06}	Set I_{06}^{IN}	Branch Network n_{06}^{IN}
(A)	0	0	0	0	172 (1.2%)	Not included	Not included	None.
(B)	0	0	1	0	11 (0.1%)	Not included	Not included	None.
(C)	0	0	1	1	8 (0.1%)	Not included	Not included	None.
(D)	1	0	0	0	7,259 (51.3%)	Included	Included	Actual network in 2006 but "closing" branches that come from *de novo* branching outside home state.
(E)	1	0	1	0	1135 (8.0%)	Included	Included	Actual network in 2006 but "closing" branches that come from *de novo* branching outside home state.
(F)	1	0	1	1	324 (2.3%)	Included	Included	Actual network in 2006 but "closing" branches outside the home state that come from *de novo* or mergers.
(G)	0	1	1	0	3897 (27.5%)	Not included	Not included	None. Including these banks is redundant with type (E).
(H)	0	1	1	1	1339 (9.5%)	Not included	Included	Actual network in 2006 of bank with surviving CERT but including branches only at home state of CERT included here.
				Total	14,145 (100%)			

□ **Decomposition of the change in the empirical distributions of banks' expected deposits and risk.** Every bank that we observe in our sample is identified by a Certificate Number (CERT). After a merger, the CERT of only one of the merging banks survives. The certificate numbers of the other merging banks are cancelled and never used again. For every bank that we observe in our sample (or more precisely, for every CERT), we can define the following dummy or indicator variables: (i) *ACT* is the dummy variable that indicates that the CERT is active at year 2006; (ii) *ACTMERG* is equal to 1 iff the CERT is not active in 2006 but this CERT was involved in one or several mergers between 1995 and 2006, and in 2006 there is a surviving bank that comes from these mergers; (iii) *MERG* is the dummy variable indicating that the CERT has been involved in a merger between 1995 and 2006; and (iv) *MERGOUT* is the dummy variable indicating that the CERT has been involved in a merger between banks with different home states. For the construction of $\{I_{06}^{IN}, \mathbf{n}_{06}^{IN}\}$, we describe a bank's history during 1995–2005 using the dummy variables *ACT*, *ACTMERG*, *MERG*, and *MERGOUT*. Table A1 presents the eight possible values of these variables.[35] Histories type (A), (B), and (C) represent bank failures or exits: (A) is exit without mergers, (B) is exit with within-state mergers, and (C) represents exits with multistate mergers. Banks with either of these histories are not included in the counterfactuals I_{06}^{IN}. Histories type (D), (E), and (F) correspond to banks with CERT that is active in 2006. This bank may have not been involved in any merger (i.e., type (D)), or in within-state merger(s) only (i.e., type (E)), or in multistate merger(s) (i.e., type (F)). Finally, histories (G) and (H) represent banks with *ACTMERG* equal to one: CERT is not active in 2006, but this CERT was involved in a merger between 1995 and 2006, and the surviving CERT from that merger is active in 2006. We have two types in this category: within-state merger(s) only (i.e., type (G)), or in multistate merger(s) (i.e., type (H)).

□ **Construction of variable profits under hypothetical values of the network of branches.** Let $VP_{it}(\mathbf{n}_i) \equiv \sum_{m=1}^{M} \pi_{mt}^*(n_{im})$ be the variable profit of bank i at year t under a hypothetical vector $\mathbf{n}_i$ (i.e., not observed in the data) for the bank i's network of branches. By definition, $\pi_{mt}^*(n_{im})$ is the variable profit of a bank in market (m, t) if the bank has

[35] By definition, not all the combinations of *ACT*, *ACTMERG*, *MERG*, and *MERGOUT* are possible.

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n_{im} branches in this county. Equation (10) describes this equilibrium variable profit in a local market. We can rewrite equation (10) as:

$$\pi^*_{mt}(n_{im}) = \frac{\beta}{2}\left(\frac{\widetilde{p}_{mt}}{1+\frac{1}{1+\widetilde{\delta}(n_{im})}+\sum_{j\neq i}\frac{1}{1+\widetilde{\delta}(n_{jmt})}}\right)^2 \frac{2+\widetilde{\delta}(n_{im})}{\left[1+\widetilde{\delta}(n_{im})\right]^2},$$

where, for $j \neq i$, the value of n_{jmt} corresponds to the value observed in the data. For the construction of the counterfactual value $\pi^*_{mt}(n_{im})$, we need to know the value of the exogenous variable $\widetilde{p}_{mt}$, the parameters $\widetilde{\delta}(n)$ for any value of n, and the scale parameter β. As we have described in the second subsection of Section 6, the parameters $\widetilde{\delta}(n)$ are estimated in the regression equation for the equilibrium logarithm of deposits. The value of $\widetilde{p}_{mt}$ can be also obtained from that regression equation. More specifically, the specification of that regression equation implies that:

$$\ln(\widetilde{p}_{mt}) - \ln\left(1+\sum_{j=1}^{I_t}\frac{1}{1+\widetilde{\delta}(n_{jmt})}\right) = X_{mt}\,\alpha + e^{(1)}_m + e^{(2)}_t,$$

where X_{mt} includes observable market characteristics, and $e^{(1)}_m$ and $e^{(2)}_t$ are captured by county dummies and year dummies, respectively. The estimation of the regression model implies an estimate of the right-hand-side variable $X_{mt}\,\alpha + e^{(1)}_m + e^{(2)}_t$, and of the function $\widetilde{\delta}(.)$ such that we can easily recover an estimate of $\ln(\widetilde{p}_{mt})$ for every county-year in our data set. The scale parameter β is normalized to one.

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