# Diversification of Geographic Risk in Retail Bank Networks: Evidence from Bank Expansion after the Riegle-Neal Act

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**Abstract**

The 1994 Riegle Neal (RN) Act removed interstate banking restrictions in the US. The primary motivation was to permit geographic risk diversification (GRD). Using a factor model to measure banks' geographic risk, we show that RN expanded GRD possibilities in small states, but that few banks took advantage. Using our measure of geographic risk and an empirical model of bank choice of branch network, we identify preferences towards GRD separately from the contribution of other factors that may limit the expansion of some banks after RN. Counterfactual experiments based on the estimated structural model show that risk has a significant negative effect on bank value, but this has been counterbalanced by economies of density/scale, reallocation/merging costs, and concerns for local market power.

**Keywords:** Riegle Neal Act; Commercial banking; Oligopoly competition; Branch networks; Liquidity risk; Geographic risk diversification.

**JEL codes:** L13, L51, G21

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# 1 Introduction

Despite the rise of the internet, branching is still the most important tool that banks have to capture deposits.[1] In order 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*. Branches attract deposits and loans from local customers which have significant idiosyncratic risk. In a geographically non-diversified banking system, negative local shocks can have severe consequences on bank liquidity levels and may even lead to bank failures (Calomiris, 2000 p.22). 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 geographic risk diversification may require banks to have branches in multiple counties, or states, or possibly even multiple countries.

In this paper 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, both 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 towards 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 laid the foundation for the removal of restrictions on interstate banking and 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 ten largest banks tripled between 1994 and 2006 going from twelve percent to thirty-six percent.

Advocates of bank expansion pushed for it using geographic risk diversification as their main argument, claiming that it would provide a more stable banking system. It was believed that removing restrictions on interstate geographic expansion would be beneficial since it would allow banks to decrease the likelihood of failure by diversifying their risk over different geographic lo-

[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.

[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 et al, 1995, and Kroszner and Strahan, 1999).

cations. 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 paper 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 geographic risk diversification 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 towards geographic risk separately from the costs of geographic expansion of branch networks, 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.

Despite the importance of the industry and the regulatory change, there is almost no empirical evidence about these issues. There has been a number of papers studying the effect of RN on outcomes such as consumer welfare (Dick, 2008, and Ho and Ishii, 2010) and market valuations (Goetz, Laeven, and Levine, 2011).[4] And there is a fairly large number of studies on the effect of geographic expansion on the level of risk faced by banks. From the point of view of the empirical questions that we analyze in this paper, 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

[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, Fed Governor from 1996 to 2002, in a speech in 1996 states: *"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."* (http://www.federalreserve.gov/boarddocs/speeches/1996/19961121.htm).

[4] A number of papers have looked at the effect of liberalization of intrastate branching restrictions on different economic outcomes such as output growth (Jayartne and Strahan, 1996), volatility (Morgan, Rime, and Strahan, 2004), or income distribution (Beck, Levine, and Levkov, 2010).

[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 Elyasian 2008). Geographic diversification is usually measured as a binary variable indicating whether or not a bank is geographically diversified (Demsetz and Strahan, 1997, Dick, 2006, Akhigbe and Whyte 2003, Schmid and Walter 2008), or the number of branches (White, 1984, Hughes et al., 1996, Carlson, 2004), or a deposit dispersion index

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, since 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, and 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 3,100 US counties. We estimate this factor model using panel data on deposits at the branch level. For most counties, the estimated level of liquidity risk is quite substantial, between 0.6 and 2.3 percentage points, and diversifiable risk is between 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 towards geographic risk separately from the contribution of the costs of geographic expansion. This approach is in the spirit of Jia (2008), Holmes (2011), 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,

(Deng and Elyasiani, 2008, and Liang and Rhoades, 1991). In the case of mergers, diversification is measured by how much overlap there is between the target and the acquirer's networks (Emmons, Gilbert and Yeager, 2002, Brewer, Jackson, and Jagtiani, 2000). 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 Appendix C.

[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.

and Hortacsu (2012) and Uetake and Wanatabe (2012) use a similar approach to estimate the determinants of bank mergers. These papers 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 and 2010), Ho and Ishii (2010), and Gowrisankaran and Krainer (2011). Our paper contributes to this literature by incorporating geographic risk diversification 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 both 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 paper is structured as follows. In the next section we present the data used in our analysis along with descriptive evidence on the evolution of the US banking industry. In Section 3 we estimate a factor model and obtain our measure of geographic risk. We then use this model in Section 4 to provide empirical evidence on the possibilities for diversification and the extent to which banks take advantage of them before and after Riegle Neal. To explain these results, in Section 5 we estimate a structural model of competition between branch networks in which banks are concerned with geographic risk. Section 6 summarizes and concludes.

# 2 Data and descriptive evidence

## 2.1 Data

We focus on the period following the passage of the RN Act, specifically the period from 1994 to 2006. Counties, the primary administrative divisions for most states, are chosen as our market definition. The boundaries of counties have been generally static in recent years.[8] By contrast,

[8]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

the boundaries of cities, villages, and other incorporated locations have been far more subject to changes. In our context, a county serves as a convenient, time invariant geographic unit at which level we can easily combine the branching activities of the depository institutions with detailed local demographic, social, and economic information. Our dataset includes information from $3,100$ 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.

Our branch level information comes from the Summary of Deposit (SOD) data provided by the Federal Deposit Insurance Corporation (FDIC). The SOD dataset is collected on June 30th each year, covering all institutions insured by the FDIC, including commercial banks and saving associations. The dataset 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.[9]

The dataset does not include branch-level information on loans, and so our focus is on the geographic risk of deposits. A primary source of geographic risk comes from volatility in the total volume of deposits. 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. 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.[10] 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, while 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 towards risk reduction.

The US Census Bureau provides various data products through which we obtain detailed county level characteristics to estimate our model: (1) population counts by age, gender, and ethnic group are obtained from the Population Estimates; (2) median household income at the county level is extracted from the State and County Data Files, while income per capita is provided by the Bureau of Economic Analysis (BEA); (3) information on local business activities such as two-digit-industry level employment and number of establishments is provided by the County Business Patterns; (4) detailed geographic information, including the area and population weighted centroid of each

in the U.S., refer to the Chapter 4 of "Geographic Areas Reference Manual" of the Census Bureau, available at http://www.census.gov/geo/www/garm.html.

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

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

county, and locations of the landmarks in the US, is obtained from the Topologically Integrated Geographic Encoding and Referencing system (TIGER) dataset.[11]

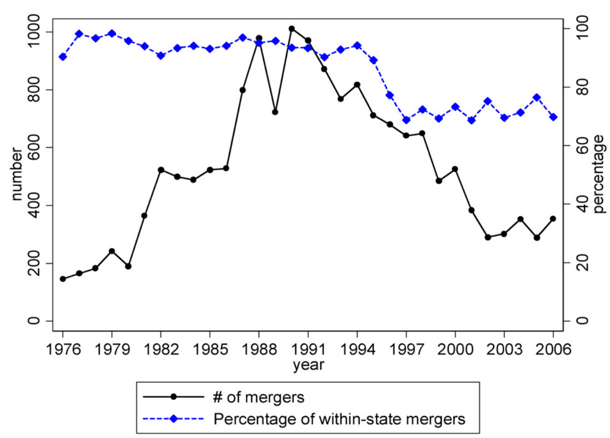
We derive bank level characteristics from balance sheets and income statement information in the banks' quarterly reports provided to the different regulatory bodies: the Federal Reserve Board (FRB)'s Report on Condition and Income (Call Reports) for commercial banks, and the Office of Thrift Supervision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

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.

## 2.2 Descriptive evidence

Tables 1 and 2 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 has been a wave of bank mergers that has increased substantially concentration ratios in the market of deposits; (ii) banks have responded to a growing demand for deposits opening more branches and keeping deposits-per-branch practically constant over time; and (iii) geographic expansion to other states has been concentrated in large banks that have used mergers/acquisitions for this expansion.

**Figure 1: Number of Mergers and % of Within-State**

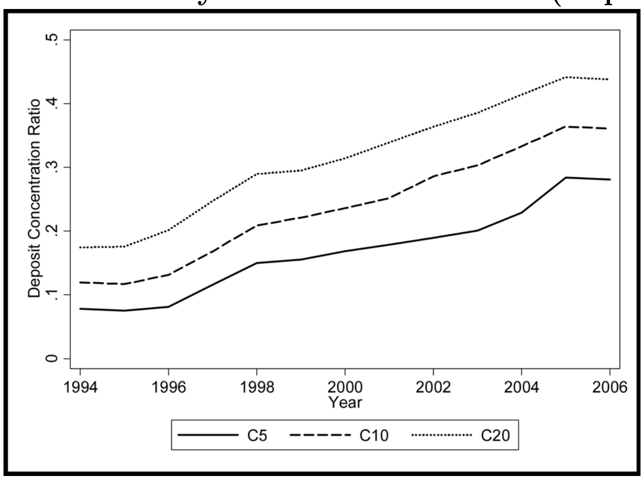



*(i) Consolidation and wave of mergers.* There has been significant consolidation of the industry, as shown by the massive and continued reduction in the number of commercial banks. The rate of decline in the number of banks slowed down during the later years of the sample. Most of the

[11] 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.

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 nine thousand banks in 2006.[12] 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 1988-92. The consequences from this merger wave can be seen in figure 2 which plots the evolution of the five-, ten-, and twenty-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.

**Figure 2: Industry Concentration Ratios (Deposits)**




*(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 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 have encouraged competition and entry of other banks. Consistent with this hypothesis, table 1 shows that banks with headquarters 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 denovo branches, despite the fact that they represent a much smaller fraction of all banks.

[12] The number of banks has continued declining between 2006 and 2010. According to a FDIC report from April 14, 2010, the number of FDIC-insured banks was 7,731. However, in contrast to our period of analysis, a significant component of the decline since 2008 is due to bank failures.

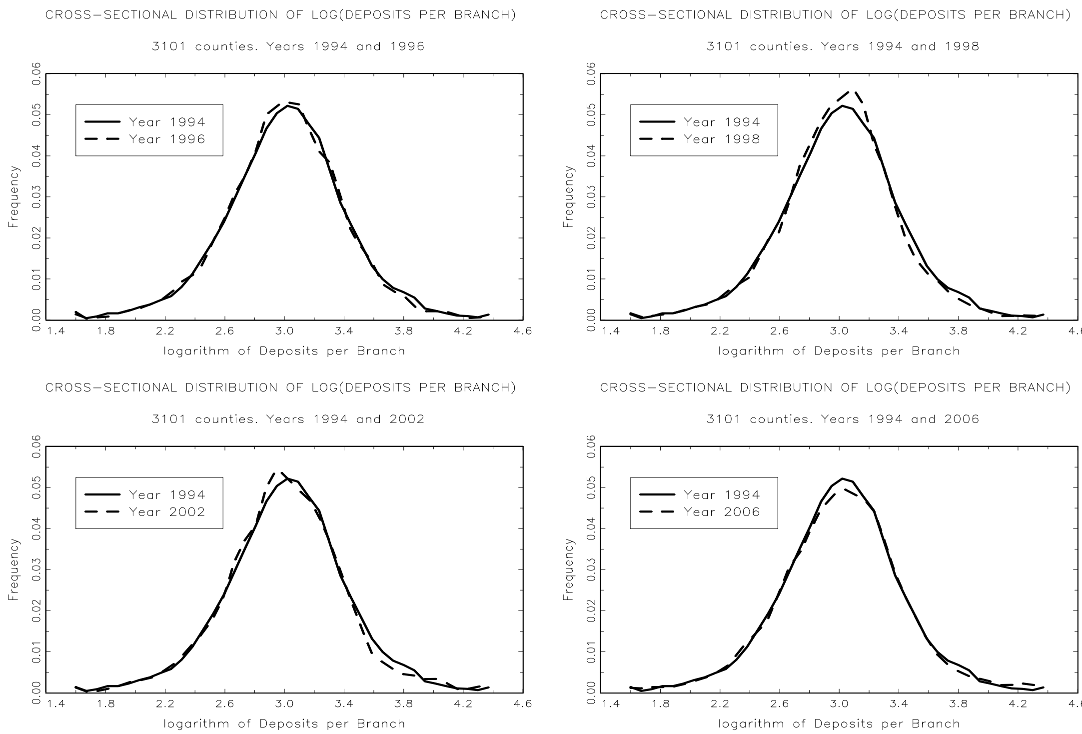
| Statistics | 1994 | 1997 | Year 2000 | 2003 | 2006 |
|---|---|---|---|---|---|
| **TABLE 1. Descriptive Statistics** | | | | | |
| **Banks:** | | | | | |
| Number of banks | 12,976 | 11,164 | 10,098 | 9,238 | 8,749 |
| Change in number of banks during last 3 years | | -1812 | -1066 | -860 | -489 |
| Openings of new banks during last 3 years | | 402 | 735 | 391 | 477 |
| Closings of banks during last 3 years due to mergers | | 2154 | 1761 | 1187 | 937 |
| Closings of banks during last 3 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 |
| % denovo branches from 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 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 $3,100$ 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, i.e., increasing the number of branches.

**TABLE 2**
**Distribution of deposits-per-branch at county level**
**Year 1994 (in millions dollars of 1990)**

| % | **Quantile** | % | **Quantile** | % | **Quantile** |
|---|---|---|---|---|---|
| *min* | 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 | | | *max* | 200.94 |

**Figure 3: Cross-Sectional Distributions of the Logarithm of Deposits per Branch**




*(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 both through the acquisition of other banks and through denovo branching. Table 1 shows that between half and two-thirds of *branch creation* is accounted for by mergers and acquisitions.[13] This proportion is between 66% and 91% in states other than the bank's headquarters, and between 33% and 50% within the same state. Therefore, while most of the out-of-state expansion has occurred through mergers, the within-state expansion has been both through mergers and denovo branching.[14]

[13] 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 $\Delta n_{imt}^{M}$ is the change due to a merger or acquisition. Appendix A describes 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 denovo branching.

[14] While almost every state immediately adopted RN to allow for inter-state banking through mergers, some states still have not chosen to permit inter-state 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 *intestate branching by merger/acquisition* between 1994 and 1996, and twenty-five states adopted it on the deadline of June 1st 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 thirteen states allowed de novo, and by 2005 twenty-two did.

**Figure 4: % of Multi-State Banks**

(by bank size as measured by number of branches)

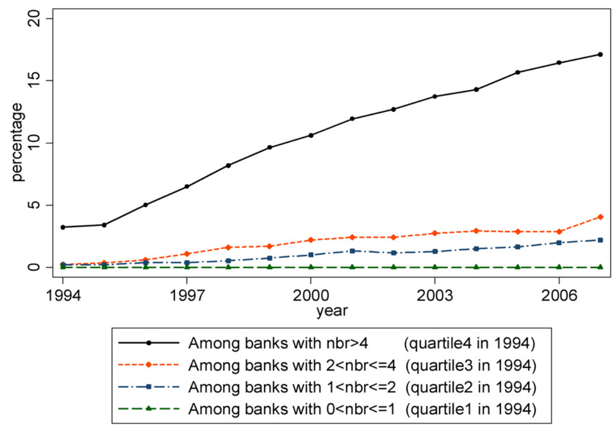



Figure 4 shows how the proportion of multi-state banks has grown steadily during the sample period. The growth is concentrated in larger banks, as measured by number of branches (a very similar pattern appears when we measure bank size by volume of deposits). Despite this growth, the proportion of "large"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

# 3 Measuring geographic risk

## 3.1 Basic framework

Our objective is to develop a measure of bank geographic risk that allows us to determine the possibilities for geographic risk diversification 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.[15] 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

[15] 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 (2010) estimate spatial models of consumer demand for retail banks. They find evidence of significant consumer disutility associated with distance traveled.

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, i.e., the number of branches at each geographic local market. The *branch network* of bank $i$ can be described as a vector $\boldsymbol{n}_{it} \equiv \{n_{imt} : m = 1, 2, ..., M\}$, 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 4 and 5 below. In section 4, 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. Though these are strong assumptions, they are useful in the sense 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 5, 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.

### 3.2 Factor model

The key feature of a factor structure model is that the variance-covariance matrix of the $M$ asset returns can be described by a simpler, lower dimensional structure. In our context, $M$ is the number of geographic local markets (e.g., counties). We postulate the following model for the logarithm of deposits per branch (hereinafter *LDPB*) in county $m$ at year $t$,

$$\ln(d_{mt}) = \alpha_m(\mathbf{X}_t) + \beta_m(\mathbf{X}_t)\ \mathbf{f}_t + u_{mt}, \tag{1}$$

where $\mathbf{X}_t$ represents a vector of variables with all the information available to banks at period $t$, $\alpha_m(.)$ is a deterministic function of $\mathbf{X}_t$, and $\beta_m(.)$ is a $1 \times F$ vector of deterministic functions of $\mathbf{X}_t$. $\mathbf{f}_t$ is an $F \times 1$ vector of random variables or *factors* that are common to all the markets. $u_{mt}$ is a random variable that is market specific. The random variables in $\mathbf{f}_t$ 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 scalar $\alpha_m(\mathbf{X}_t)$ is the expected value of $\ln(d_{mt})$ conditional on $\mathbf{X}_t$. The terms $\beta_m(\mathbf{X}_t)\ \mathbf{f}_t$ and $u_{mt}$ are the unexpected or risk components. The vector of factors $\mathbf{f}_t$ represents the systematic risk that affects every geographic market. These $F$ factors are i.i.d. over time, without loss of generality they have zero mean, and the $F \times F$ variance-covariance matrix is $\mathbf{\Sigma_f}$. The effect of these systematic risk factors may vary across markets. The effect in market $m$ and period $t$ is $\beta_m(\mathbf{X}_t)\ \mathbf{f}_t$, where $\beta_m(\mathbf{X}_t)$ is the vector of *factor loadings*. The scalar random variable $u_{mt}$ represents the market-specific idiosyncratic risk.

An important issue in the specification and estimation of this factor model, and consequently in our measure 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. If our model is not flexible enough to account for the actual heterogeneity across counties in the level and evolution of deposits, then we will spuriously measure as diversifiable risk something that is known ex-ante to banks, but does not represent risk for these firms. To deal with this issue, our specification includes county fixed effects both in the mean of deposits and in the variance of diversifiable risk. Furthermore, the vector $\mathbf{X}_t$ includes many observable variables at the county level, such as the lagged depend variable, lagged number of branches, log population, log income-per-capita, log total-employment, log number of business establishments, employment shares of nineteen 2-digit industries, and establishment shares of nineteen 2-digit industries (i.e., 44 variables for each county-year). The specification of the conditional mean is $\alpha_m(\mathbf{X}_t) = \alpha_m^{(0)} + \mathbf{X}_{mt}\ \boldsymbol{\alpha}^{(1)}$, where $\mathbf{X}_{mt} \subset \mathbf{X}_t$ is a $1 \times K$ vector of observable variables, $\alpha_m^{(0)}$ is a county-fixed-effect, and $\boldsymbol{\alpha}^{(1)}$ is a vector of parameters. Factor loadings depend on the observable variables $\mathbf{X}_{mt}$ according to the linear system $\beta_m(\mathbf{X}_t) = \mathbf{X}_{mt}\ \mathbf{B}$, where $\mathbf{B}$ is a $K \times F$ matrix.

A potentially important constraint for banks' geographic risk diversification 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 $\beta_m(\mathbf{X}_t)\ \mathbf{f}_t$. 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 less 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 $1,000$ miles away from the center of county $m$. And so on. The spatial autoregressive process of $u_{mt}$ can be represented using expression

$u_{mt} = \rho_1 \ \tilde{u}_{mt}^{(1)} + \rho_2 \ \tilde{u}_{mt}^{(2)} + ... + \rho_S \ \tilde{u}_{mt}^{(S)} + e_{mt}$, where $\tilde{u}_{mt}^{(s)}$ is the mean value of the shock $u$ in band $s$ around county $m$, $\rho_1$, $\rho_2$, ..., $\rho_S$ 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:

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

where $\mathbf{u}_t$ is the $M \times 1$ vector $(u_{1t}, u_{2t}, ..., u_{Mt})'$; similarly, $\mathbf{e}_t$ is the vector $(e_{1t}, e_{2t}, ..., e_{Mt})'$; 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 $e_{mt}$, i.e., $var(e_{mt}|\mathbf{X}_t) = \exp\left\{\delta_m^{(0)} + \mathbf{X}_{mt} \ \boldsymbol{\delta}^{(1)}\right\}$, 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 LDPB for each county at year $t$ has the following vector of expected values and variance-covariance matrix:

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

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

### 3.3 Estimation of the factor model

Appendix B provides a detailed description of the estimation procedure. Table 3 summarizes the estimation of the factor model. The number of observations in the estimation is $37,200$ ($3,100$ counties times 12 years). The vector of market characteristics $\mathbf{X}_{mt}$ includes the 44 variables at the county level that we have described above. The goodness-of-fit of the model is excellent: the R-square coefficient for the within-groups regression is 0.54, and the equation in levels (including fixed effects) has an R-square of 0.87.

Panel 3(a) includes estimates of parameters $\boldsymbol{\alpha}^{(0)}$ and $\boldsymbol{\alpha}^{(1)}$ in expected LDPB. We report estimates of the most significant parameters $\boldsymbol{\alpha}^{(1)}$, and quantiles in the empirical distribution of county fixed effects $\alpha_m^{(0)}$. There is substantial persistence in LDPB even after controlling for county fixed effects: the parameter estimate for the lagged dependent variable is 0.7382 (s.e. = 0.0067). LDPB increases significantly with county population, income per capita, and employment. The employment share of industries such as Management, Real Estate, IT, and Retail, have a positive effect on LDPB. The distribution of county fixed effects shows significant heterogeneity in expected LDPB across counties that is not explained by observable variables.

**TABLE 3. Estimation of Factor Model for log-deposits-per-branch**

**Panel (3a): Arellano-Bond estimation of parameters in Mean $\boldsymbol{\mu}^D$**

| $\boldsymbol{\alpha}^{(1)}$ Parameters | | $\boldsymbol{\alpha}_m^{(0)}$ Fixed effects parameters | |
|---|---|---|---|
| **Variable** | **Estimate (s.e.)** | **Probability** | **Quantile** |
| Lagged log deposits | 0.7383 (0.0067)* | minimun | -1.449 |
| Lagged log # branches | 0.0343 (0.0071)* | Quantile 5% | -1.284 |
| log Population | 0.0990 (0.0141)* | Quantile 25% | -1.134 |
| log Income | 0.0734 (0.0140)* | Quantile 50% | -1.042 |
| Employ. share Management | 0.1875 (0.1564) | Quantile 75% | -0.978 |
| Employ. share Real Estate | 0.1642 (0.1690) | Quantile 95% | -0.792 |
| Employ. share IT | 0.1332 (0.1485) | maximum | -0.269 |
| Employ. share Retail | 0.1014 (0.1534) | | |

Note: The specification includes 44 explanatory variables. Here we report the most significant estimates.

**Panel (3b): Systematic risk: $\sqrt{\mathbf{X}_t \mathbb{V}\left(\widehat{\gamma}_t\right) \mathbf{X}_t'}$. 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 Employ. Shares | 0.0836 (14.3 %) | | |

**Panel (3c): Spatial Autoreggressive Process of $u_{mt}$**

| Parameter | Estimate (s.e.) | Parameter | Estimate (s.e.) |
|---|---|---|---|
| $\rho$ ($<200$ *miles*) | 0.3573 (0.0229) | $\rho$ (400 *to* 1,000 *miles*) | 0.1115 (0.0544) |
| $\rho$ (200 *to* 400 *miles*) | 0.2699 (0.0321) | $\rho$ ($>1,000$ *miles*) | -0.1510 (0.2883) |

**Panel (3d): Parameters in variance of Diversifiable risk**

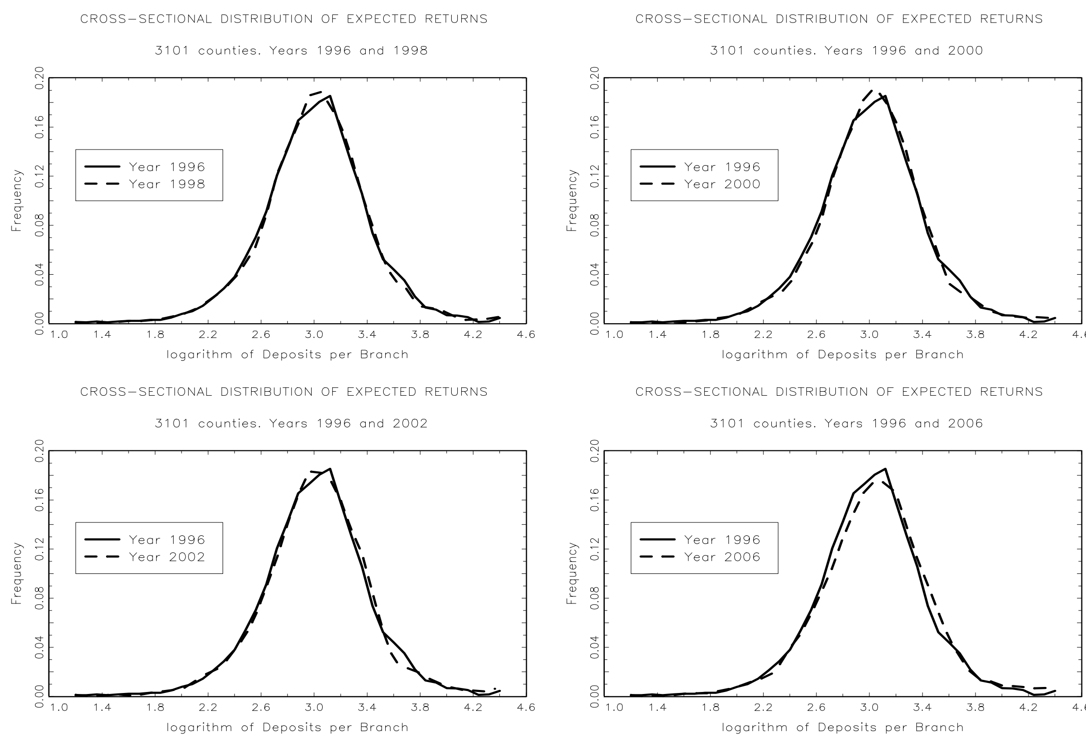
| $\boldsymbol{\delta}^{(1)}$ Parameters | | $\boldsymbol{\delta}_m^{(0)}$ Fixed effects parameters | |
|---|---|---|---|
| **Variable** | **Estimate (s.e.)** | **Probability** | **Quantile** |
| Lagged log deposits | -0.2102 (0.1137) | minimun | -10.150 |
| Lagged log # branches | -0.2169 (0.1405) | Quantile 5% | -8.327 |
| log Population | 0.2273 (0.2823) | Quantile 25% | -7.486 |
| log Income | 0.0275 (0.0934) | Quantile 50% | -6.951 |
| | | Quantile 75% | -6.428 |
| Note: The specification includes 44 explanatory variables. | | Quantile 95% | -5.692 |
| Here we report the most significant estimates. | | maximum | -3.963 |

Panel 3(b) presents summary statistics on the estimation of systematic risk, as measured by $\sqrt{\mathbf{X}_{mt}\ \mathbb{V}(\widehat{\gamma}_t)\ \mathbf{X}'_{mt}}$. 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 2-digit industries (14%) also represent important contributions to systematic risk.[16]

Panel 3(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 $1,000$ miles, and more than $1,000$ miles. There is strong spatial correlation in the residuals, that declines with distance and becomes insignificant for distances greater than $1,000$ miles.

Panel 3(d) presents the estimated parameters in the model for the variance of the diversifiable risk. 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.

**Figure 5: Cross-Sectional Distribution of Expected log-Deposits-per-Branch**




Figures 5, 6, and 7 present the cross-sectional distributions of expected LDPB, 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, i.e., counties with high levels of systematic or diversifiable risk in 1996 also have high levels of risk in 2006.

[16] The decomposition of the contribution of different factors does not sum to 100% because non-zero covariances.

For most counties, the estimated level of deposit risk is substantial. For 90% of the counties, systematic risk is between 0.6 and 2.3 percentage points (i.e., percentiles 10 and 90, respectively) and diversifiable risk is between 1.1 and 3.1 percentage points. 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 return on equity (ROE). We illustrate this point using a simple model in Appendix C. Therefore, differences between banks' geographic diversification may explain a substantial part of their differences in profitability.

**Figure 6: Cross-Sectional Distributions of Diversifiable Risk**

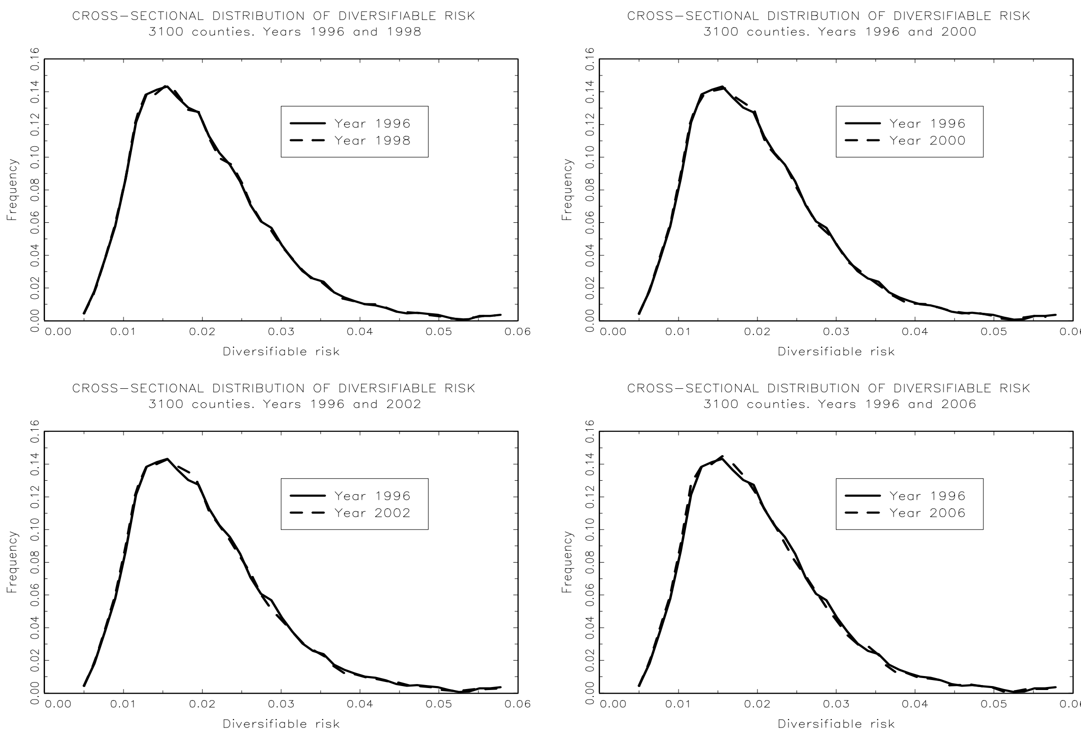
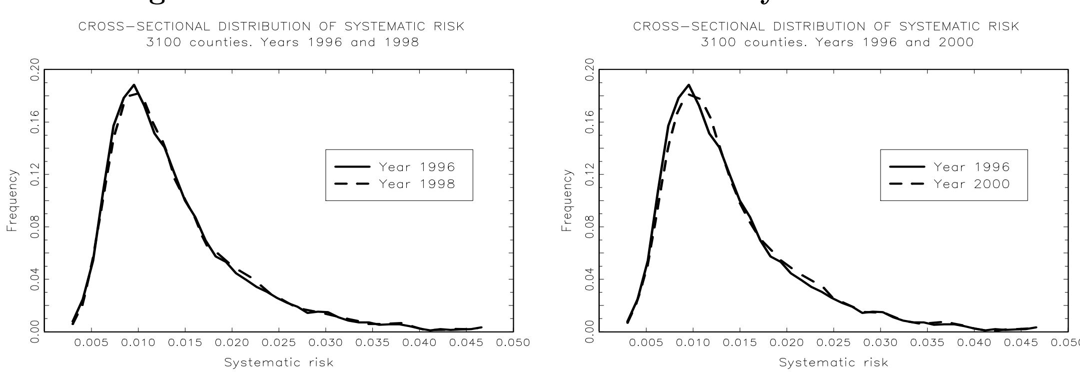
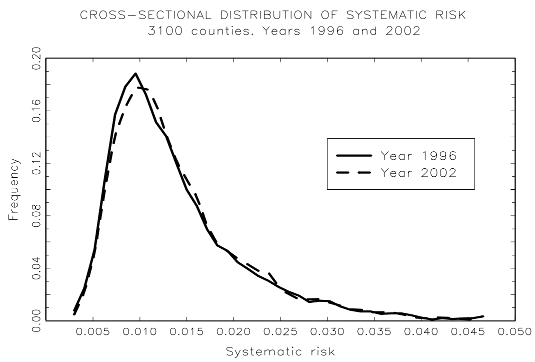
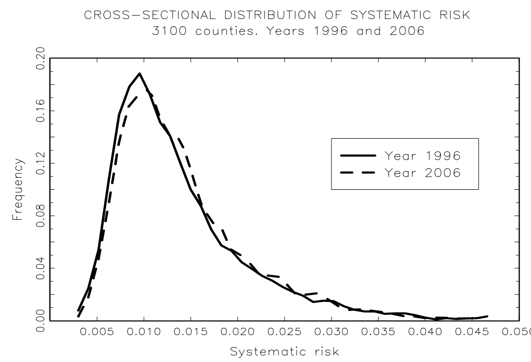



**Figure 7: Cross-Sectional Distributions of Systematic Risk**






# 4 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.

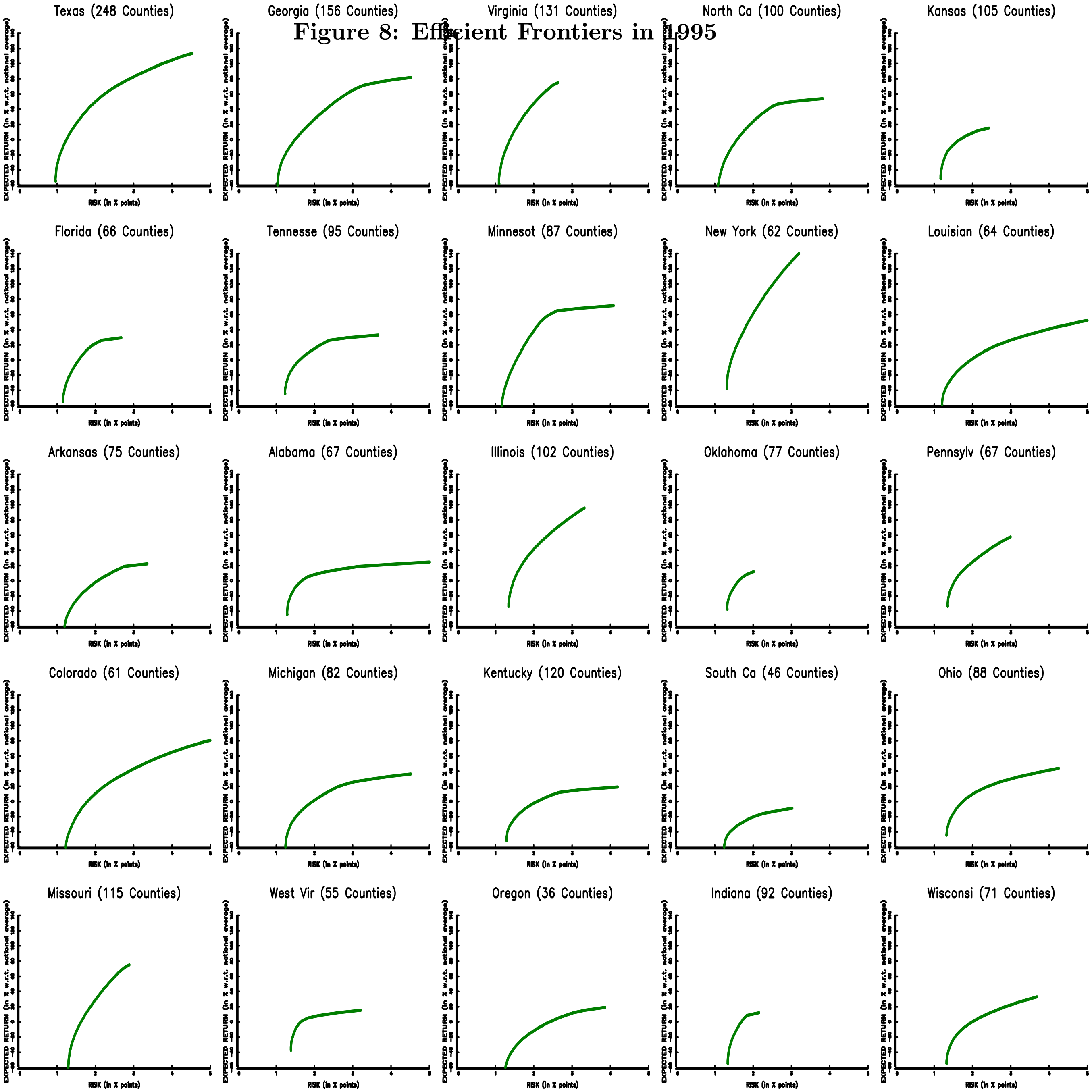
## 4.1 Geographic Risk Diversification possibilities–Efficient frontiers

We start by considering the possibilities for geographic risk diversification (GRD) available to banks before and after RN. We use the factor model estimated above to construct efficient frontiers for each state in 1995 before the banks could take advantage of RN, and a single efficient frontier in 2006 assuming banks can locate branches anywhere in the United States. A bank *portfolio* is its branch network $\mathbf{n}_{it}$. Let $\mathbf{w}_{it} \equiv \{w_{imt} : m = 1, 2, ..., M\}$ 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 or profitability of a branch is measured by LDPB. By *expected LDPB* and *risk* of a bank branch portfolio we mean $R_{it} \equiv \mathbf{w}_{it}' \, \boldsymbol{\mu}_t$ and $S_{it} \equiv \sqrt{\mathbf{w}_{it}' \, \mathbf{\Omega}_t \, \mathbf{w}_{it}'}$, respectively. A portfolio lying on the efficient frontier represents the combination of counties in a given state offering the best possible expected LDPB for given level of risk. For the moment, the construction of these efficient frontiers is based on the assumption that all portfolios of counties are feasible, i.e. that banks can open 'many' branches in a state and locate them optimally throughout all of the counties. Given this, the Efficient Frontier informs us as to the possibilities of diversification only for large banks.[17]

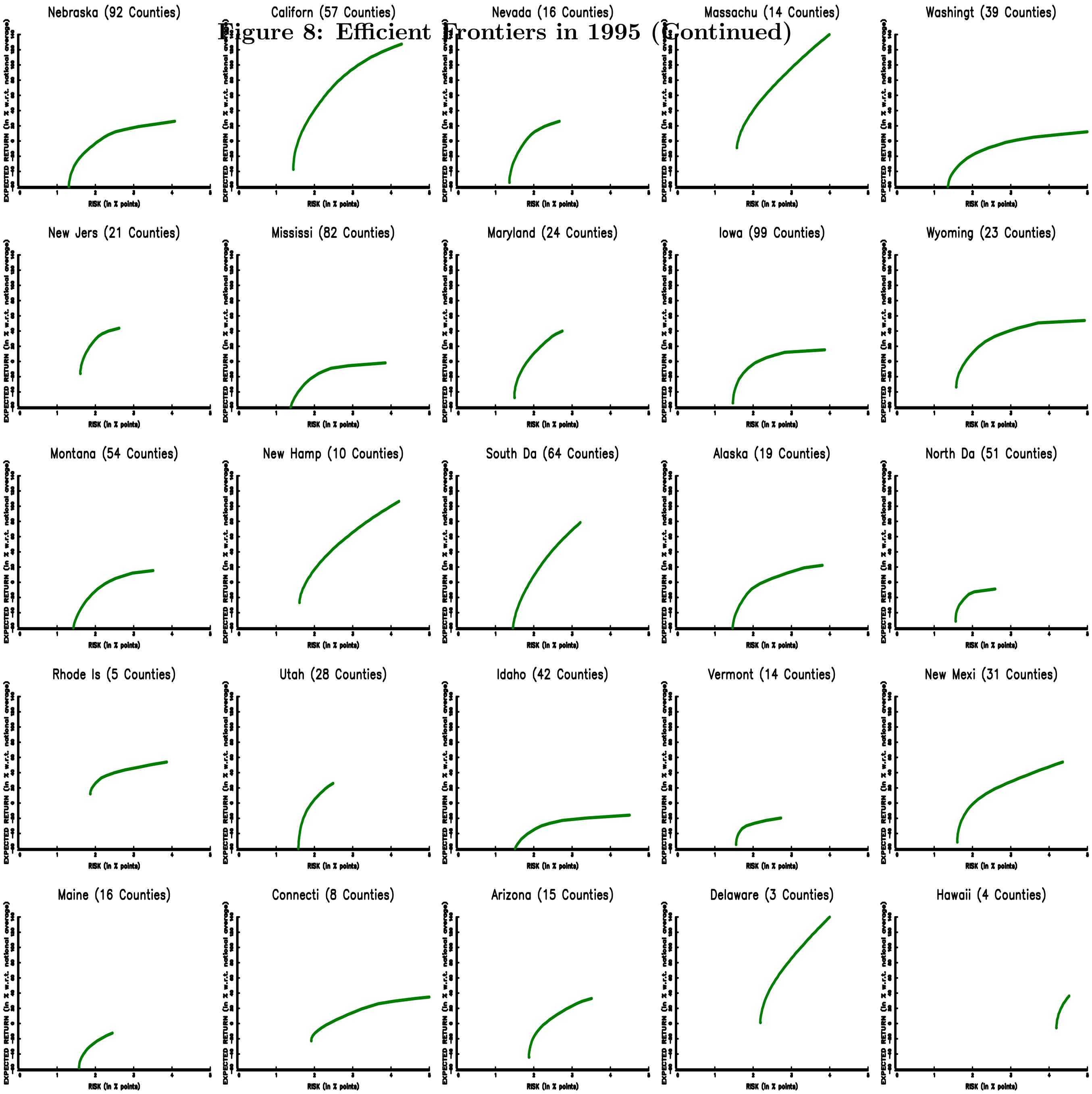
*(a) Prior to Riegle Neal.* Figure 8 presents the efficient frontiers for each of the states ordered according to their maximum LDPB-to-risk ratios. The figure reveals very significant cross-State heterogeneity in the pre RN frontiers. The observed heterogeneity implies that the possibilities for geographic risk diversification for very large banks differed significantly across states. Therefore, in some states large banks could easily achieve a diverse portfolio of branches while in others they would have been constrained by the limitations of the pre RN regulations.

[17] More precisely, in the construction of these frontiers we assume that the weight of county $m$ in the portfolio of bank $i$, as measured by the ratio $n_{imt}/(\sum_{m'=1}^{M} n_{im't})$ is a continuous variable. This is a good approximation to the actual choice of a bank only when its total number of branches is large.

**Figure 8: Efficient Frontiers in 1995**



## Figure 8: Efficient Frontiers in 1995 (Continued)




*(b) Post Riegle Neal.* Figure 9 plots the 2006 Efficient Frontier assuming banks can locate branches anywhere in the US. 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 4 reports the percentage change in maximum LDPB-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,[18] 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.

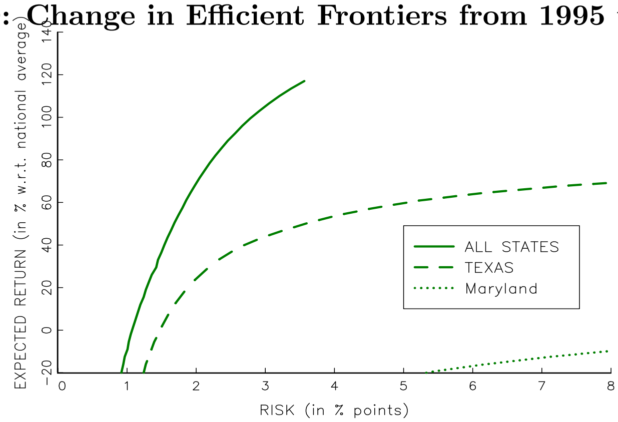
TABLE 4. Change in Efficient Frontiers after Riegle-Neal: 1995-2006
% change in Maximum LDPB-to-Risk ratio (Max RR) and Minimum Risk (Min Risk)
States sorted by Max RR in 1995

| | Year 1995 | | % change 95 to 06 | | | Year 1995 | | % change 95 to 06 | |
|---|---|---|---|---|---|---|---|---|---|
| | Max | Min | Max | Min | | Max | Min | Max | Min |
| State (# counties) | RR | Risk | RR | Risk | State (# counties) | RR | Risk | RR | 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 "(06-95)/95 (%)" report the percentage change between 1995 and 2006 in maximum possible Return to Risk Ratio (MaxRR) and minimum possible risk (MinRisk) along the state efficient frontiers.

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

**Figure 9: Change in Efficient Frontiers from 1995 to 2006**




### 4.2 Geographic Risk Diversification possibilities–small banks

*(a) Prior to Riegle Neal.* The efficient frontiers presented above describe the geographic risk diversification possibilities only for large banks since 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 LDPB-to-risk ratio taking as *given* the location of the previous existing branches. We then ask the following questions: (i) What is the maximum LDPB-to-risk ratio that this bank can reach when it adds $n-1$ branches optimally? (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 LDPBs and variance matrix of 1995. Then we construct the following statistics at the state level: the median of the maximum LDPB-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, i.e., MinRisk. We compare these statistics between states to learn about heterogeneity in the possibilities of GRD for small banks prior to RN. Table 5 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 it becomes almost negligible when this number is greater than ten, 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 1 to 5 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).

TABLE 5. Feasible Minimum Risk for Small Banks before Riegle-Neal. Year 1995
States sorted by Maximum Return-to-Risk Ratio in the Efficient Frontier in 1995

| | Minimum Risk with n branches (%)[1] | | | | | Minimum Risk with n branches (%)[1] | | | |
|---|---|---|---|---|---|---|---|---|---|
| State (# counties) | n = 1 | n = 5 | n = 10 | MinRisk[2] | State (# counties) | n = 1 | n = 5 | n = 10 | MinRisk[2] |
| 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 (1): We assume that banks can only expand within its home state and minimize risk when adding a new branch.
Note (2): MinRisk represents the minimum risk with a continuum of branches. It is the same as minimum risk in Table 4 above.

*(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 banks can only

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

**TABLE 6. Effect of RN on the possibilities of GRD of small banks**

| | TEMaxRR | TEMinRisk | | TEMaxRR | TEMinRisk |
|---|---|---|---|---|---|
| State (# counties) | %ΔRR | %Δrisk | State (# counties) | %ΔRR | %Δrisk |
| 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 LDPB-to-risk ratio and risk in the Thought Experiment for banks with 5 branches before and after the RN act.

1. "TEMaxRR": Thought experiment when a bank sequentially add branches to maximize LDPB-to-risk ratio.
2. "TEMinRisk": Thought experiment when a bank sequentially add branches to minimize risk.
3. $\%\Delta RR = (post\_RR - pre\_RR)/pre\_RR * 100$. This percentage change is calculated for each county. The reported number is the median value of counties for each state.
4. $\%\Delta Risk = (post\_Risk - pre\_Risk)/pre\_Risk * 100$. This percentage change is calculated for each county. The reported number is the median value of counties for each state.

Table 6 presents the percentage difference in maximum LDPB-to-risk ratio (MaxRR) and minimum risk (MinRisk) pre RN and post RN for a bank with only 5 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%).

### 4.3 Actual bank portfolios

So far we have talked only about the possibilities for geographic risk diversification 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.

**Figure 10A: Distribution of Banks' Expected log-deposits-per-branch in 1995**

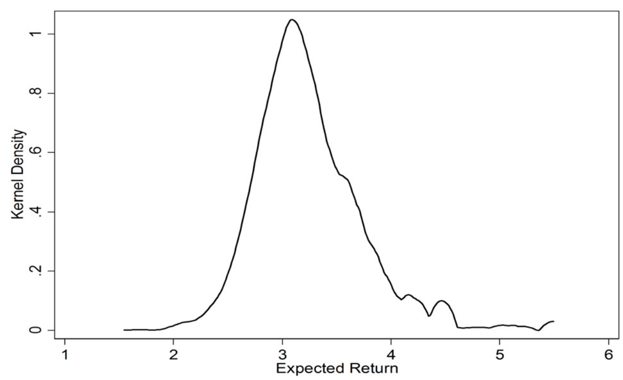
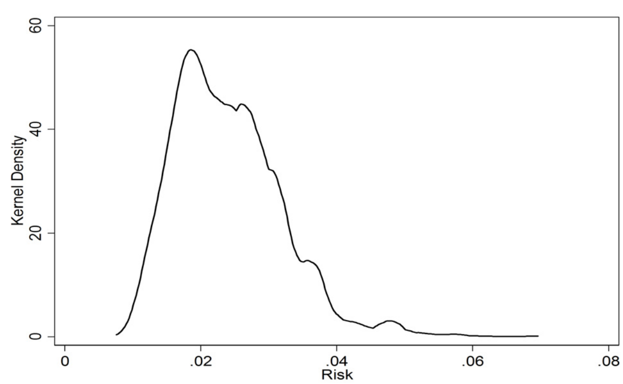



**Figure 10B: Distribution of Banks' Risk of deposits in 1995**




We start by looking at actual banks' portfolios prior to RN. Using the vector of means and the variance matrix of deposits per-branch of 1995, we obtain the expected LDPB, $R_i$, and the risk, $S_i$, for each bank in 1995. In figures 10A and 10B we present the cross-sectional distributions of banks' expected LDPBs and risk. The comparison of these 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 LDPBs at bank and county level are very similar.

Figure 11 presents the cross-sectional distribution of expected LDPB (panel A), and risk level (panel B) for 1995 and for 2006. We can see that there is some improvement in expected LDPB (i.e., the median value goes from 3.17 to 3.19, an improvement of 2 percentage points), but almost no reduction in risk (i.e., the median value goes from 0.0230 to 0.0226, a reduction in 0.04 percentage points).

**Figure 11A: Distribution of banks' expected log-deposits-per-branch: 1995 and 2006**

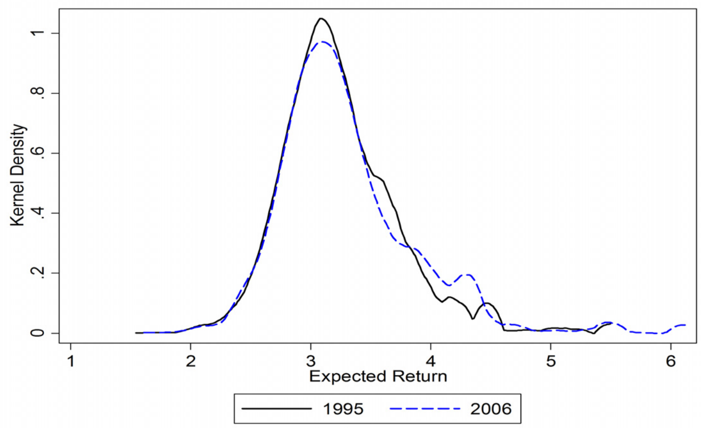
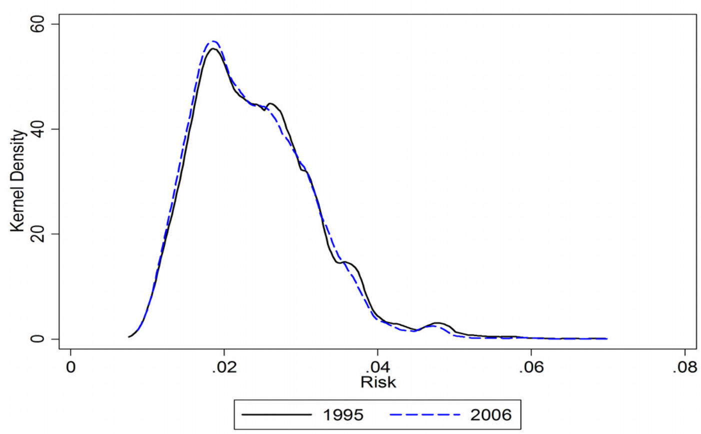



**Figure 11B: Distributions of banks' risk of deposits: 1995 and 2006**




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. In order 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 LDPB between 1995 and 2006.

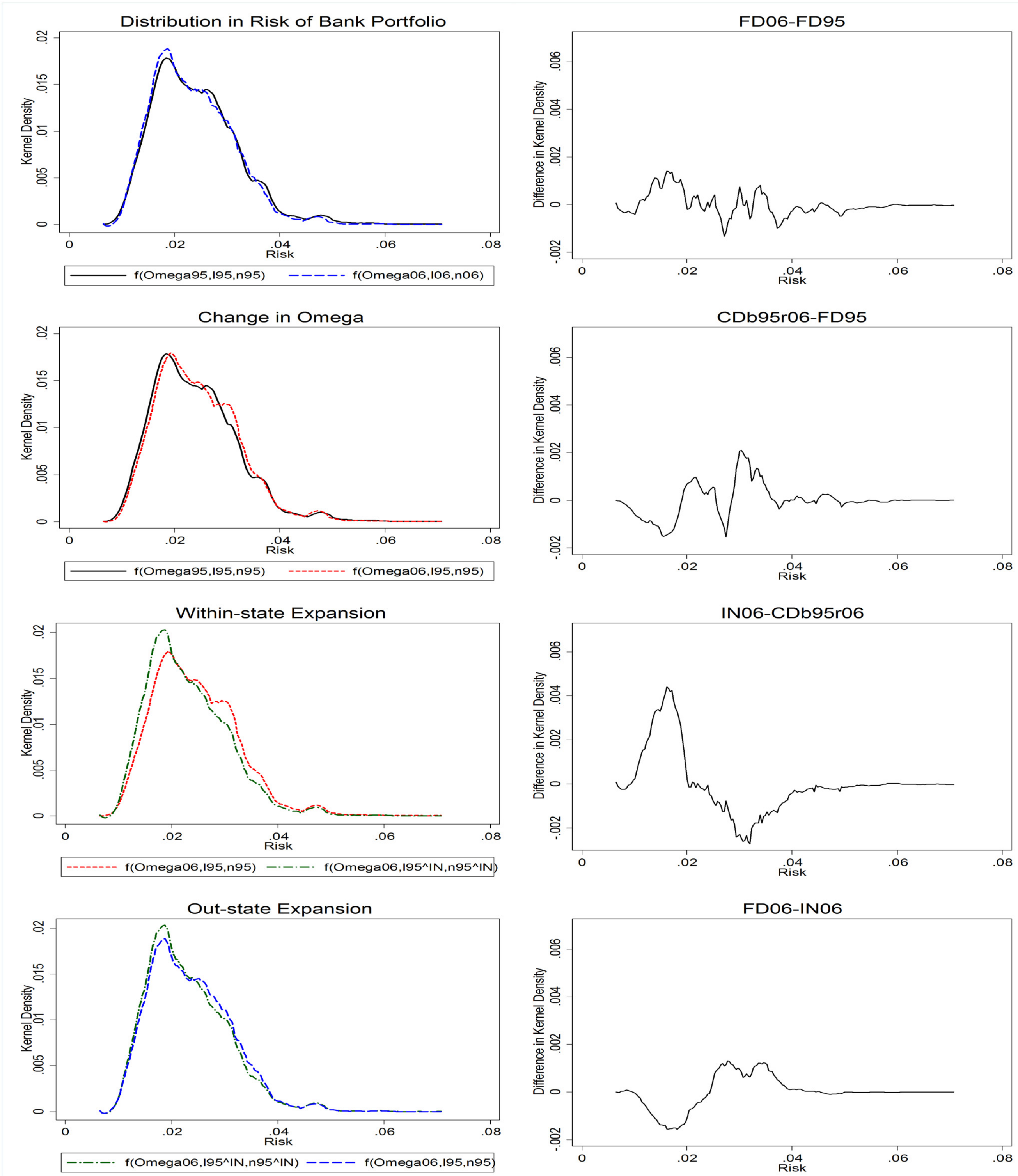
A cross-sectional distribution of banks' risk, either factual or counterfactual, can be described as a vector of banks' risks $\mathbf{S} \equiv \{S_i : i \in I\}$ where $I$ is a set of banks, and $S_i$ is the risk of bank $i$. Since the risk of bank $i$ is determined by the function $S_i = \sqrt{\mathbf{n}_i' \, \mathbf{\Omega} \, \mathbf{n}_i}$, 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, i.e., $\mathbf{S}_t = f(\mathbf{\Omega}_t, I_t, \mathbf{n}_t)$. 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:

$$\begin{aligned} \mathbf{S}_{06} - \mathbf{S}_{95} &= [\ f(\mathbf{\Omega}_{06},\ I_{95},\ \mathbf{n}_{95}) - f(\mathbf{\Omega}_{95},\ I_{95},\ \mathbf{n}_{95})\ ] && \Rightarrow \text{ Contribution of change in } \mathbf{\Omega} \\ &+ \left[\ f(\mathbf{\Omega}_{06},\ I_{06}^{IN},\ \mathbf{n}_{06}^{IN}) - f(\mathbf{\Omega}_{06},\ I_{95},\ \mathbf{n}_{95})\ \right] && \Rightarrow \text{ Contribution of within-state expansion} \\ &+ \left[\ f(\mathbf{\Omega}_{06},\ I_{06},\ \mathbf{n}_{06}) - f(\mathbf{\Omega}_{06},\ I_{06}^{IN},\ \mathbf{n}_{06}^{IN})\ \right] && \Rightarrow \text{ Contribution of out-state expansion.} \end{aligned} \tag{4}$$

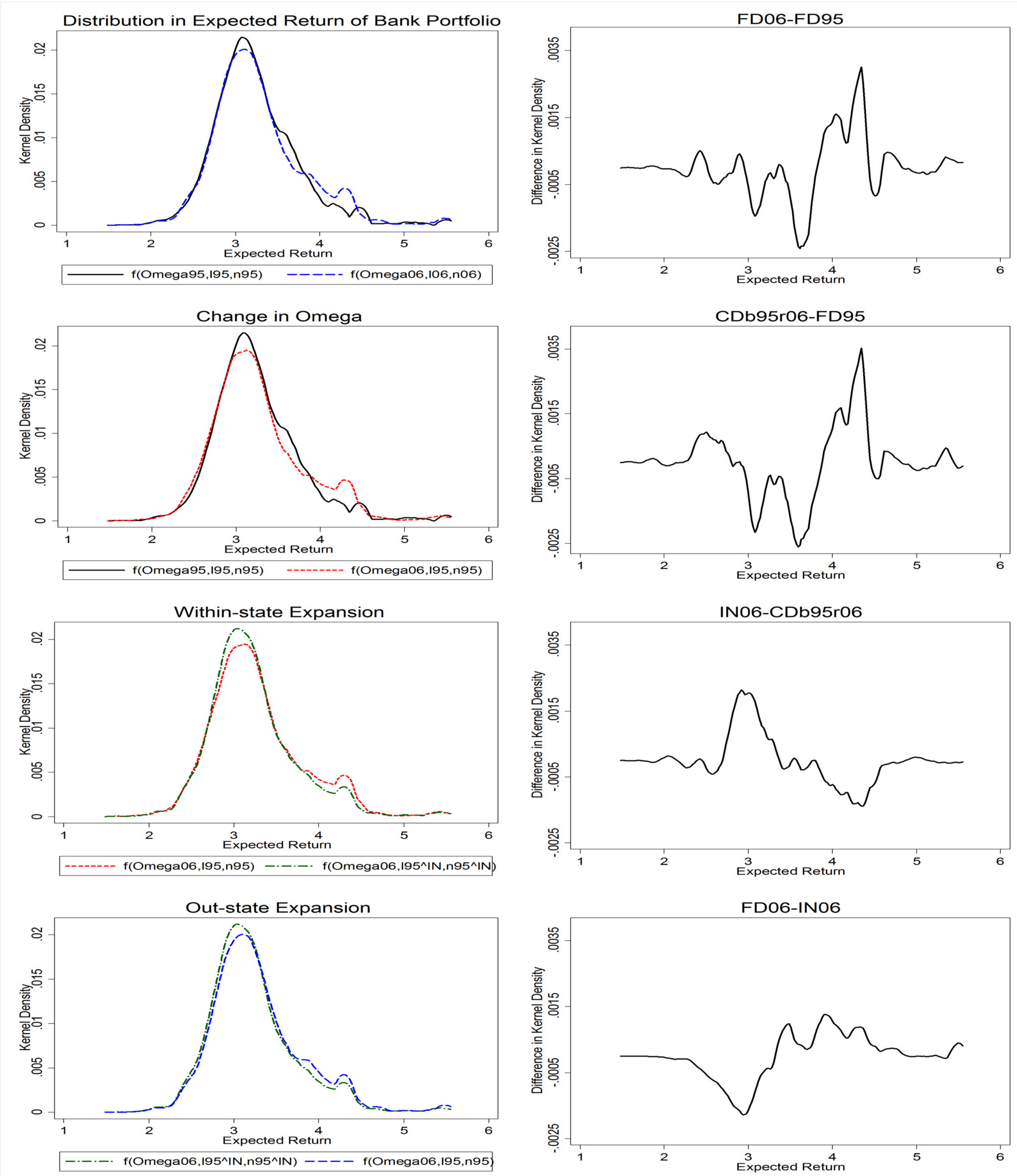
This decomposition captures three different *ceteris paribus* effects. The first term measures the contribution of the change in matrix $\mathbf{\Omega}$ between 1995 and 2006. $f(\mathbf{\Omega}_{06}, I_{95}, \mathbf{n}_{95})$ is the counterfactual distribution that we would observe if the set of banks and their branch networks 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, i.e., 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 denovo branching.[19]

[19]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 assumption in Appendix E.

**Figure 12: Decomposition of change in distribution of banks' risk: 1995-2006**



## Figure 13: Decomposition of change in distribution of banks' expected deposits-per-branch: 1995-2006



Results are presented in figures 12 and 13 for the distributions of risk and expected LDPB, respectively. The first row shows the actual change in the distribution. Rows 2 to 4 present the contribution to the actual change of the variation in the omega matrix, within-state expansion, and out-state expansion, respectively. These figures show that out-of-state branch expansion did not have any contribution to the reduction in bank risk but it contributed to increase expected LDPBs. Almost all 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 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 since, as we have shown above, following RN deposits became much more concentrated in a small number of banks. One possibility is that, while 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: (a) large banks have increased very substantially their LDPBs, regardless of their initial LDPB in 1995; and (b) overall, 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 LDPBs. For expansion within state, the expected LDPBs actually become more concentrated on lower values, suggesting that some large banks expand within state to achieve geographic risk diversification at the cost of lowering expected LDPB.

**Figure 14: Decomposition of change in distribution of banks' risk: 1995-2006**

Each bank observation is weighted by the bank total volume of deposits

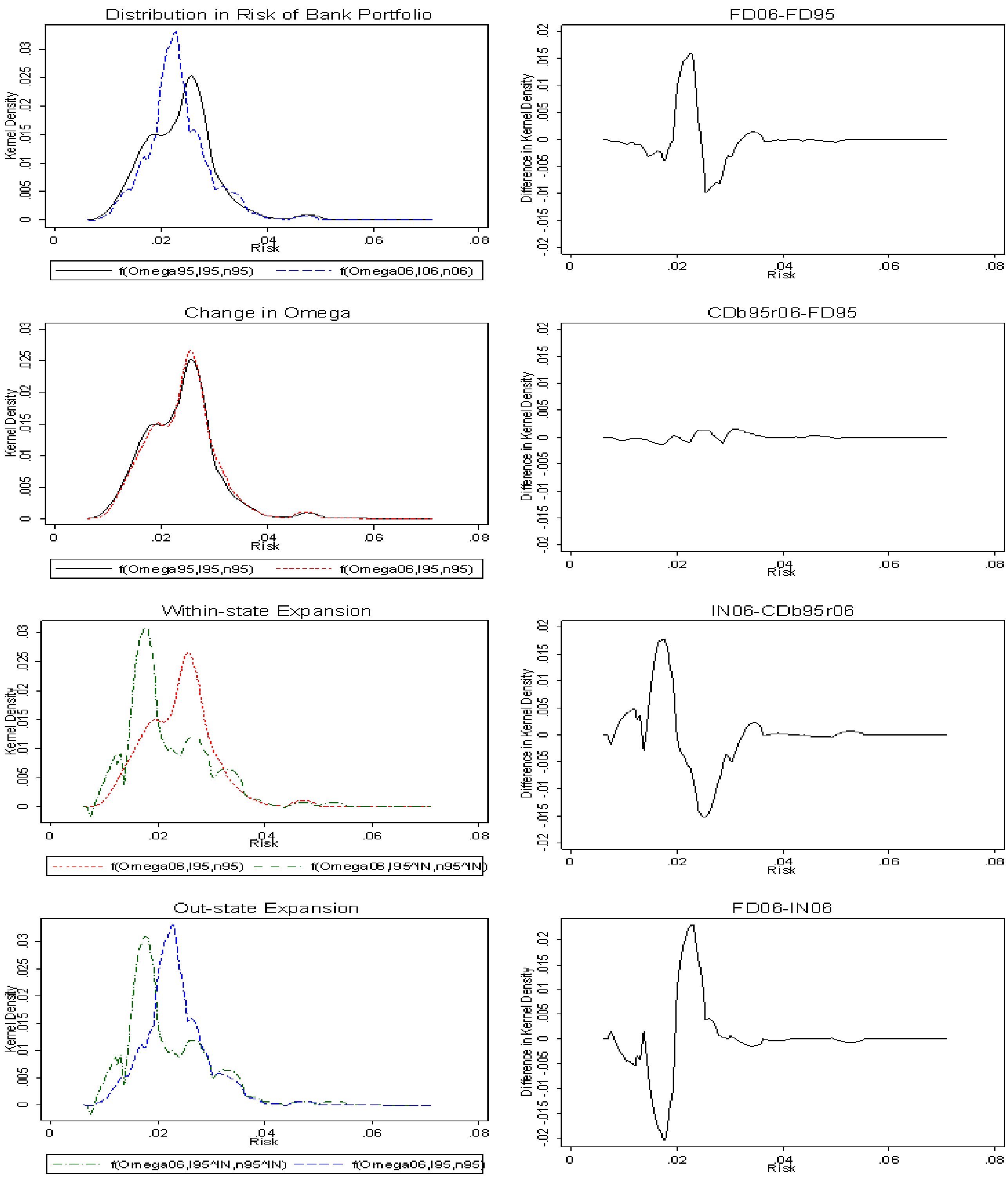
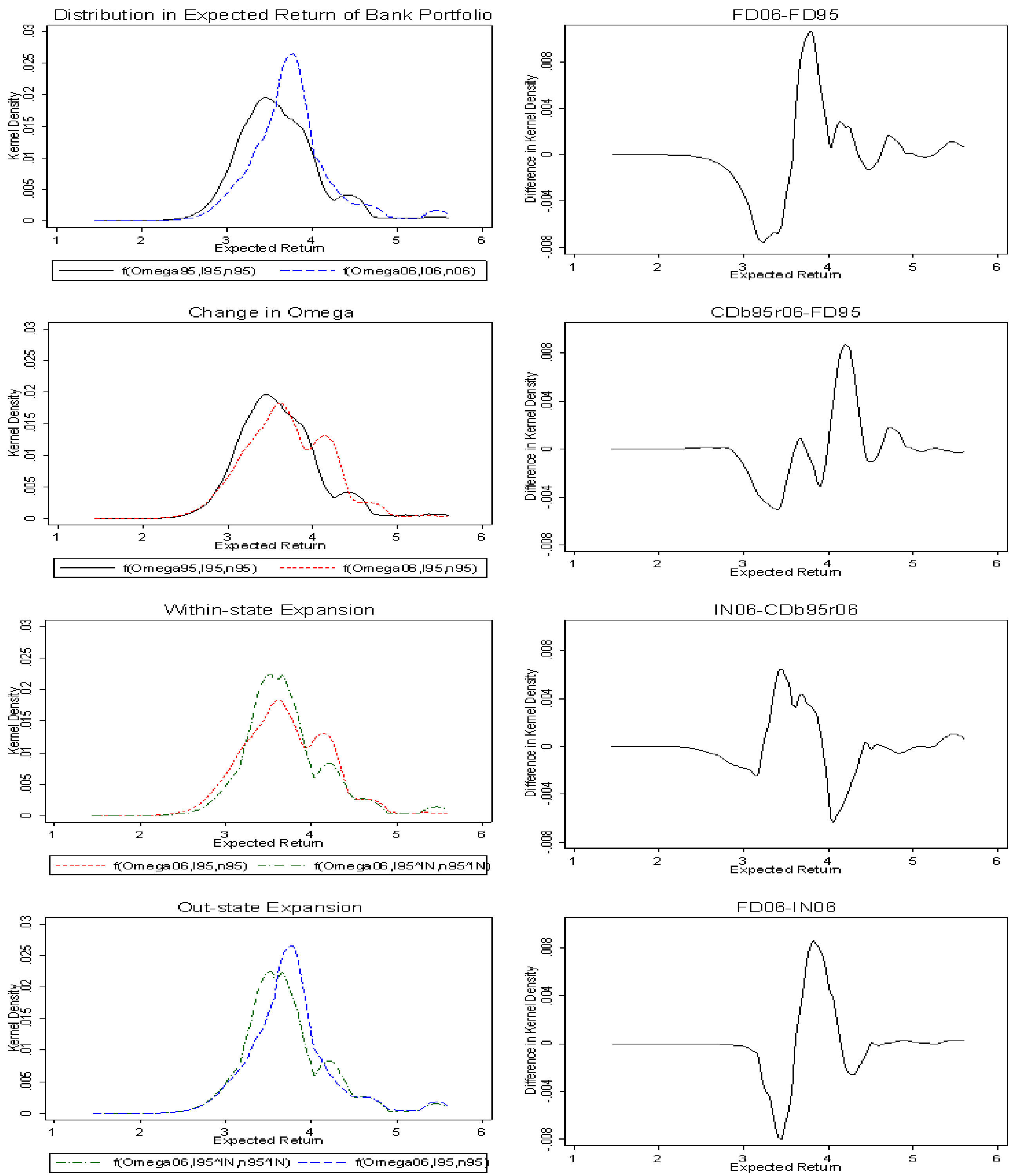


**Figure 15: Decomposition of change in distribution of banks' expected deposits-per-branch: 1995-2006**

Each bank observation is weighted by the bank total volume of deposits



# 5 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, 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 where banks are (potentially) concerned with geographic risk. We use this model to identify banks' concern for geographic diversification of risk separately from other factors that influence branch network expansion.[20]

## 5.1 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 in section 5.3, 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, i.e., $D_{imt} = f_d(n_{imt}, \mathbf{n}_{mt}, X_{mt})$ and $\pi_{imt} = f_\pi(n_{imt}, \mathbf{n}_{mt}, X_{mt})$. For the purpose of this paper, we are interested in the equilibrium functions $f_d$ and $f_\pi$ 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 that is consistent with the evidence shown in section 2 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 interest rate of deposits, $\alpha_{mt}$ 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:

$$\pi_{imt} \quad = \quad (p_{mt} - r_{mt})\ \ D_{imt} - C_{mt}\left(D_{imt}, n_{imt}\right). \tag{5}$$

$p_{mt}$ represents the return from the best lending options in this market, and we assume that it is exogenously given. $C_{mt}\left(D, n\right)$ represents the variable cost of the bank for managing a volume

[20] 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.

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 $\gamma_{mt}$ is an exogenous cost shifter, and $\delta(n)$ is a positive-valued and decreasing function that captures diseconomies of scale at the branch level, i.e., 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[21]

$$D^*_{imt} = \left( \frac{p_{mt} - \alpha_{mt} - \gamma_{mt}}{\beta(I^*_{mt} + 1)} \right) \left( \frac{1}{1 + \frac{\delta(n_{imt})}{\beta}} \right), \tag{6}$$

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

$$\pi^*_{imt} = \beta \left[ 1 + \frac{\delta(n_{imt})}{2\beta} \right] (D^*_{imt})^2. \tag{7}$$

The value of the parameter $\delta(n)/\beta$ 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, i.e., in a market with $\delta(n)/\beta = 0$, having more than one branch is a waste of resources. When $\delta(n)/\beta$ is strictly positive, 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 branches of the competitors.

## 5.2 Estimation of the model of local market competition

Based on the equilibrium amount of deposits in equation (6), we consider the following regression model for the logarithm of deposits: $\ln(D_{imt}) = \alpha_0 + \alpha_1 \ln(D_{imt-1}) + X_{mt}\ \alpha - \ln\left(1 + \frac{\delta(n_{imt})}{\beta}\right) + e_{imt}$, 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 $\alpha$ and the function $\delta(n)/\beta$. 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 $\delta(n)/\beta$, 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 deposits when the number of branches goes from $n-1$ to $n$. By definition, there is the following relationship between $\sigma$ and $\delta/\beta$:

[21] 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, $D_i = \left(\frac{p-r-\gamma}{\beta}\right)\left(\frac{1}{1+\delta(n_i)/\beta}\right)$. Aggregating over banks and solving for the equilibrium value of market deposits, we obtain that $D = \left(\frac{p-\alpha-\gamma}{\beta}\right)\frac{I^*}{I^*+1}$.

$\sigma(n) = -\ln(1 + \delta(n)/\beta) + \ln(1 + \delta(n-1)/\beta)$. Therefore, we can represent the regression model for deposits as follows:

$$\ln(D_{imt}) = \alpha_0^* + \alpha_1 \ln(D_{imt-1}) + X_{mt}\alpha + \sum_{j=2}^{n_{\max}} 1\{n_{imt} \geq j\}\ \sigma(j) + e_{imt}, \tag{8}$$

where the new constant term is $\alpha_0^* \equiv \alpha_0 - \ln(1 + \delta(1)/\beta)$, $1\{.\}$ 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 $X_{mt}$, $1\{n_{imt} \geq 2\}$, ..., $1\{n_{imt} \geq n_{\max}\}$ and slope parameters $\alpha$, $\sigma(2)$, ..., $\sigma(n_{\max})$. More precisely, we impose the restriction that $\sigma(n)$ is constant for $n \geq 20$.[22]

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, $e_{imt} = e_{im}^{(1)} + e_t^{(2)} + e_{imt}^{(3)}$, where each of these error components can be correlated with the endogenous regressors $1\{n_{imt} \geq j\}$. Under the assumption that $e_{imt}^{(3)}$ 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, $\Delta e_{imt}^{(3)} \equiv e_{imt}^{(3)} - e_{im,t-1}^{(3)}$, 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 $e_{imt}^{(3)}$ can be tested by looking at the second-order serial correlation in 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 $\{\ln(D_{ims}), 1\{n_{ims} \geq j\} : s = t-2, ..., t-5\}$ and the vector of exogenous regressors $\Delta X_{mt}$.

Table 7 presents our GMM estimates of the semi-elasticity parameters, $\sigma(n)$, and of the parameters associated with the most significant explanatory variables in $X_{mt}$. For the sake of comparison, we also report estimates from a fixed-effect method with county-bank fixed effects. 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. The Hansen-Sargan test of over-identifying restrictions has a p-value of 0.0429 which does not represent a clear rejection of these restrictions. The parameter estimates show that the volume of deposits of a bank increases by 22% when the number of branches goes from 1 to 2. This semi-elasticity declines slowly with the number of branches and it 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. These relatively modest values for

[22] Note that the no identification of the 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 $\delta(n)/\beta$ using the recursive formula $\delta(n)/\beta = \left[\frac{1+\delta(n-1)/\beta}{\exp\{\sigma(n)\}}\right] - 1$ for any $n \geq 2$. This normalization is innocuous.

the semi-elasticities show substantial cannibalization between the branches of a bank in the same county. Therefore, it seems that the existence of multiple branches of the same bank in a local market should be explained by the reduction in variable costs, and by competition and strategic complementarity with other banks' branch choices.

**Table 7: Relationship Between Number of Branches and Deposits for a Bank in a County**

*Dependent variable:* $\ln(D_{imt})$

| **Parameter (or explanatory variable)**[3] | **Fixed-Effects Estimator**[1] *Estimate* | *(s.e.)* | **Arellano-Bond GMM Estimator**[1,2] *Estimate* | *(s.e.)* |
|---|---|---|---|---|
| $\sigma(2)$ | 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) |
| $\sigma(n > 20)$ | 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 2nd order correlation (p-value)* | - | | -0.325 (0.745) | |
| *Hansen-Sargan test OIR [d.o.f.] (p-value)* | - | | 846 [777] (0.0429) | |

Note 1: Standard errors robust of heteroskedasticity and serial correlation.

Note 2: Two-step GMM estimator. Equation in first differences. Set of instruments include lagged endogenous variables from lag t-2 to lag t-5.

Note 3: The estimated model includes free semi-elasticity parameters $\sigma(n)$ for any any $n$ between 2 and 20

### 5.3 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, $\mathbb{E}(V_{it}|\mathbf{X}_t)$, that has the following four components:[23]

$$\mathbb{E}(V_{it}|\mathbf{X}_t) \quad = \quad \sum_{m=1}^{M} \pi^*_{imt} - FC_{it}(\mathbf{n}_{it}) - AC_{it}(\mathbf{n}_{it}, \mathbf{n}_{it-1}) - \rho_{it} \; \Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t). \tag{9}$$

*(a) Variable profit.* The first term, $\sum_{m=1}^{M} \pi^*_{imt}$, is the sum of variable profits from all the local markets where the bank is active. Given the local market equilibrium described above, a bank's total variable profit is equal $\beta \Pi_{it}(\mathbf{n}_{it})$ where $\Pi_{it}(\mathbf{n}_{it}) \equiv \sum_{m=1}^{M} \left[1 + \frac{\delta(n_{imt})}{2\beta}\right] (D^*_{imt})^2$. Given our estimation of the deposit equation presented above, we can construct estimates of $\Pi_{it}(\mathbf{n}_i)$ for any hypothetical value of the number of own stores $\mathbf{n}_i$. In the construction of these hypothetical variable profits, we impose the Nash assumption and keep the number of stores of the other banks at their observed values.

*(b) Fixed operating costs.* The second term, $FC_{it}(\mathbf{n}_{it})$, consists of the fixed cost of operating the branch network. 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, i.e., $\theta_1^{FC}$ [#branches] $+\theta_2^{FC}$ [#branches]$^2$, and of the average distance to the bank's headquarters, i.e., $\theta_3^{FC}$ [#branches * distance-to-HQs] $+\theta_4^{FC}$ [#branches * (distance-to-HQs)$^2$].

*(c) Adjustment costs.* The third 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 denovo branching. It depends on the change in total number of branches of the bank, on the form of expansion (through merger or denovo branching), and on whether the expansion is within or outside the headquarters state of the bank, i.e., $\theta_1^{AC}$ [# new branches via denovo, within HQs state] + $\theta_2^{AC}$ [# new branches via denovo, outside HQs state] + $\theta_3^{AC}$ [# new branches via merger, within HQs state] + $\theta_4^{AC}$ [# new branches via merger, outside HQs state].

*(d) Cost of liquidity shortage.* The fourth term in a bank's profit is the expected *cost of liquidity shortage*, as defined in Appendix C, where $\Pr(D_{it} \leq L_i - E_i \mid \mathbf{X}_t)$ is the probability of liquidity

[23] It seems reasonable to think 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 structural model of network choice is a challenging problem for computational reasons, and we have not addressed that problem in this paper. Instead, following a large literature on empirical models of market entry, our specification of the value function in equation (9) can be interpreted as a "semi-structural" specification where expected future payoffs are approximated using a linear function of current payoffs.

shortage, $D_{it}$ is the total volume of deposits of bank $i$, $L_i$ and $E_i$ represent the bank's illiquid assets and equity, respectively, and $\rho_{it}$ is a variable that represents the cost of *liquidity shortage.* 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 $\Phi_{it}$, 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 ($ETD \equiv E_i/D_i$). The values of the ratios $LTD$ and $ETD$ are determined using average historical data during this sample period, i.e., $LTD = 150\%$ and $ETD = 15\%$. Therefore, we have that $\Phi_{it} = \Phi\left(\frac{\tau\ \mathbb{E}(D_{it}|\mathbf{X}_t)}{\sqrt{\mathbb{V}(D_{it}|\mathbf{X}_t)}}\right)$, with $\tau \equiv LTD - ETD - 1 = 0.35$. For the exogenous variable $\rho_{it}$ that captures the cost of liquidity shortage, we consider that it is proportional to the variable profit of the bank. Therefore, the expected value of a bank network becomes $\mathbb{E}(V_{it}|\mathbf{X}_t) = (1 - \bar{\rho}\ \Phi_{it})\ \mathbb{E}(\sum_{m=1}^{M} \pi_{imt}|\mathbf{X}_t) -\ FC_{it} -\ AC_{it}$, where $\Phi_{it}$ is the probability of liquidity shortage, and the parameter $\bar{\rho}$ can be interpreted as an ad-valorem tax, i.e., a probability of liquidity shortage $\Phi_{it}$ is equivalent to a tax $\bar{\rho}\ \Phi_{it}$ on variable profits. Therefore, we have that $\mathbb{E}\left(V_{it} \mid \mathbf{X}_t\right) = \beta\ \Pi_{it}(\mathbf{n}_{it})\left[1 - \bar{\rho}\ \Phi_{it}\right] -\ FC_{it}(\mathbf{n}_{it}) -\ AC_{it}(\mathbf{n}_{it}, \mathbf{n}_{it-1})$.

For the estimation of this model, it is convenient to represent the expected value of a bank as $\mathbb{E}\left(V_{it} \mid \mathbf{X}_t\right) = W_{it}(\mathbf{n}_{it})\ \boldsymbol{\theta} + \varepsilon_{it}(\mathbf{n}_{it})$, where $W_{it}(\mathbf{n}_{it})$ is the vector of known functions $\{\Pi_{it}(\mathbf{n}_{it})$, $-\Phi_{it}\Pi_{it}(\mathbf{n}_{it})$, [#branches], [#branches]$^2$, [#branches * distance-to-HQs], [#branches * (distance-to-HQs)$^2$], [# new branches via denovo, within HQs state], [# new branches via denovo, outside HQs state], [# new branches via merger, within HQs state], [# new branches via merger, outside HQs state]$\}$, $\boldsymbol{\theta}$ is the vector of parameters $(\beta, \bar{\rho}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_1^{AC}, \theta_2^{AC}, \theta_3^{AC}, \theta_4^{AC})'$, and $\varepsilon_{it}(\mathbf{n}_{it})$ represents other factors that are unobservable to the researcher but known to the bank.

### 5.4 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:

$$\mathbf{n}_{it} = \arg\max_{\mathbf{n} \in A_{it}} \left\{W_{it}(\mathbf{n})\ \boldsymbol{\theta} + \varepsilon_{it}(\mathbf{n})\right\}, \tag{10}$$

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). 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 $A_{it}$, $W_{it}(\mathbf{n}_{it})\ \boldsymbol{\theta}^0 + \varepsilon_{it}(\mathbf{n}_{it}) \geq W_{it}(\mathbf{n})\ \boldsymbol{\theta}^0 + \varepsilon_{it}(\mathbf{n})$. These inequalities still hold when we integrate the two sides over the distribution of $\varepsilon_{it}$ conditional on the observable predetermined state variables $\mathbf{X}_t$:

$$\mathbb{E}\left( W_{it}(\mathbf{n}_{it})\frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} + \frac{\varepsilon_{it}(\mathbf{n}_{it})}{\sigma_\varepsilon} - W_{it}(\mathbf{n})\frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} - \frac{\varepsilon_{it}(\mathbf{n})}{\sigma_\varepsilon} \mid \mathbf{X}_t \right) \geq 0, \tag{11}$$

where $\sigma_\varepsilon$ 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 endogenous selection. The selection term $\mathbb{E}(\varepsilon_{it}(\mathbf{n}) \mid \mathbf{X}_t)$ 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 $\varepsilon_{it}(\mathbf{n})/\sigma_\varepsilon \leq K < \infty$, i.e., 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:

$$\mathbb{E}\left(\mathbf{Z}_{it} \; \left[ \left(W_{it}(\mathbf{n}_{it}) - W_{it}(\mathbf{n})\right) \frac{\boldsymbol{\theta}^0}{\sigma_\varepsilon} + K \right]\right) \geq 0, \tag{12}$$

where $\mathbf{Z}_{it} = \{\mathbf{Z}_{hit} : h = 1, 2, ..., H\}$ is a vector of instruments, i.e., known functions of predetermined state variables $\mathbf{X}_t$ and of exogenous bank characteristics. The most attractive feature of our approach is that it does not really on any particular parametric assumption about the distribution of $\varepsilon's$ or about its correlation structure 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. Since the number of inequalities (of possible values of $\mathbf{n}$) is extremely large, we consider only values of $\mathbf{n}$ in a subset $C_{it}$ of 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:

$$\hat{\boldsymbol{\theta}}_{MIE} \;\; = \;\; \arg\min_{\widetilde{\boldsymbol{\theta}}} \sum_{h,\mathbf{n}\in C_{it}} \left[ \max\left\{ -\sum_{i=1}^{I_t} \sum_{t=1}^{T} \mathbf{Z}_{hit} \left[ \left(W_{it}(\mathbf{n}_{it}) - W_{it}(\mathbf{n})\right) \; \widetilde{\boldsymbol{\theta}} + K \right] \; ; \; 0 \right\} \right]^2 . \tag{13}$$

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 $K \in [4, 6]$, i.e., the upper bound in the support of the unobservables can be up to six times the standard deviation.

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 observation $(i, t)$ in our sample, the set $C_{it}$ contains the following branch networks for bank $i$: (a) the actual choice, $\mathbf{n}_{it}$; (b) opening (closing) up to five branches in headquarters-county (HQs) (up to 10 choice alternatives); (c) merged with the largest, or second largest, or third largest bank (in terms of number of branches) in HQs (up to 3 alternatives); (d) same as (b) and (c) but in county closest to HQs, and in county with the highest expected LDPB, in county with the lowest risk, and in county with the lowest correlation, within the HQs state (up to 52 alternatives); (e) same as (b), (c), and (d) but for counties in states that share a border with the HQs state (up to 65 alternatives); and (f) same as (b), (c), and (d) but for counties in states that do not share a border with the HQs state (up to 65 alternatives). Each subset $C_{it}$ contains a maximum of 196 choice alternatives, but in most of the cases the number of choice alternatives is around one hundred.

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, or/and 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 8 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 $\bar{\rho}$ 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 millions, and the cost per branch increases with the number of branches, i.e., the cost per branch of a network with 10 branches is

$2.68M$. 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 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 $28.2M$ if the average distance is 100 miles, and this cost increases to $34.4M$ if the average distance is 500 miles.

**Table 8**
**Estimation of Bank Network Costs and Benefits based on Moment Inequalities. Years 1995-2006**

| Parameter | Estimate | (s.e.)[(1)] |
|---|---|---|
| $\beta/\sigma_\varepsilon$ (in million \$) | 3.2135 | (0.8720) |
| Cost of Insolvency Parameter $\overline{\rho}$ | 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. Denovo branching* | | |
| Denovo Branch Creation within state (in million \$ per branch) | -1.3325** | (0.2803) |
| Denovo Branch Creation out 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 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 state × small bank dummy (in million \$ per new branch) | -2.4309** | (0.6767) |
| Number of observations (#banks) | 120,812 | (14,127) |

Note 1. Bootstrap standard errors resampling banks and using 500 bootstrap samples with 14,127 banks each.

The estimated costs of denovo 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 $1.3M$ within the state, and it increases to $2.1M$ if the new branch is open in a state different from the bank headquarters. The estimated merging cost per acquired branch is smaller than the cost of denovo 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 3 branches or less.

### 5.5 Counterfactual experiments

Based on these estimates of the model, we implement two counterfactual experiments to illustrate the contributions of GRD and economies of density to the geographic expansion of US banks. In the first experiment, we shut down the effect of GRD by making the parameter $\bar{\rho}$ equal to zero. In the second experiment we eliminate economies of density by fixing $\theta_3^{FC}$ and $\theta_4^{FC}$ to zero. We simulate banks' network choices under these hypothetical scenarios and making unobservables $\varepsilon$ equal to zero, and we compare these predictions with those using the actual parameter estimates and with $\varepsilon' s$ also equal to zero. We focus on the following predictions: (a) average annual probability of adding new branches (through denovo or merger) outside the home county; (b) average annual probability of adding new branches outside of the home state; and (c) average annual change in geographic deposit risk. We distinguish between small banks (i.e., three branches or less), medium (4 to 20 branches), and large banks (21 or more branches).[24]

Table 9 presents summary statistics from these experiments. In the first experiment, 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 increasing the number of branches within the home state goes from 5.2% to 1.8%, and the probability of expanding out of the home state becomes practically zero. As a result, annual change in the deposit risk of these small banks goes from $-0.07$ to $-0.03$ percentage points. Therefore, banks concern for GRD is a very important factor to explain the observed patterns of expansion of small banks in the data. In the second experiment, we find that shutting down economies of density has a very 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 both 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.

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 out state either through denovo branching or through mergers.

[24] Note that values 4 and 20 are the percentiles 65 and 95, respectively, in the distribution of bank number of branches. Therefore, this classification divides banks into three groups with 65%, 30%, and 5%, respectively, of the bank-year observations in the data.

**Table 9**
**Counterfactual Experiments using Model of Branch Networks**

| Statistic | Actual Value | Model Prediction | Exp. 1 $\bar{\rho}=0$ | Exp. 2 $\theta_3^{FC}=\theta_4^{FC}=0$ |
|---|---|---|---|---|
| **Small banks (#branches$\leq$ 3)** | | | | |
| Prob. new branches outside home county (%) | 4.97 | 5.20 | 1.83 | 6.47 |
| Prob. new branches outside home state (%) | 0.36 | 0.43 | 0.02 | 0.75 |
| Annual change in deposit risk (pctage points) | -0.062 | -0.071 | -0.032 | -0.082 |
| **Medium banks (4 $\leq$#branches$\leq$ 20)** | | | | |
| Prob. new branches outside home county (%) | 16.93 | 14.66 | 13.68 | 16.50 |
| Prob. new branches outside home state (%) | 1.92 | 1.64 | 1.63 | 4.71 |
| Annual change in deposit risk (pctage points) | -0.034 | -0.028 | -0.026 | -0.045 |
| **Large banks (#branches$\geq$ 21)** | | | | |
| Prob. new branches outside home county (%) | 43.77 | 38.18 | 37.98 | 45.39 |
| Prob. new branches outside home state (%) | 17.34 | 15.83 | 15.80 | 18.79 |
| Annual change in deposit risk (pctage points) | -0.002 | 0.000 | 0.000 | -0.001 |

## 6 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 non-diversified 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. Since the residential crisis hit Georgia particularly hard, its non-diversified 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 LDPBs. Together, these findings suggest that the policy has not achieved its stated objective.

In order 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 towards 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 A: Branch creation through mergers and denovo branches.

Let $n_{imt}$ be the number of branches of bank $i$ in county $m$ at year $t$. And let $\Delta n_{imt}$ be the net change in the number of branches between years $t-1$ and $t$, i.e., $\Delta n_{imt} \equiv n_{imt} - n_{imt-1}$. We can represent this net change as the sum of two components: $\Delta n_{imt} = \Delta n_{imt}^{M} + \Delta n_{imt}^{D}$, where $\Delta n_{imt}^{M}$ is the net change due to a merger or acquisition, and $\Delta n_{imt}^{D}$ is the net change due to denovo 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 clear that the total net change $\Delta n_{imt}$ should be attributed to denovo branching, i.e., $\Delta n_{imt} = \Delta n_{imt}^{D}$. 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, $\Delta n_{imt}^{M}$ is equal to the total number of branches that the acquired bank (or banks) had in county $m$ at year $t-1$, and $\Delta n_{imt}^{D}$ is constructed as the residual change $\Delta n_{imt}^{D} = \Delta n_{imt} - \Delta n_{imt}^{M}$.

## APPENDIX B: Estimation of Factor Model

The vector of factors $\mathbf{f}_t$ can be observable to the researcher or not. We have estimated both observable and unobservable factor models for our data, and we have obtained very similar results. Here we describe the estimation of the factor model with unobservable factors.[25] Combining equation (1) with our specification of functions $\alpha_m(\mathbf{X}_t)$ and $\beta_m(\mathbf{X}_t)$, we can represent the factor model as $\ln(d_{mt}) = \alpha_m^{(0)} + \mathbf{X}_{mt} \left[\boldsymbol{\alpha}^{(1)} + \mathbf{B}\ \mathbf{f}_t\right] + u_{mt} = \alpha_m^{(0)} + \mathbf{X}_{mt}\ \boldsymbol{\gamma}_t + u_{mt}$, where $\boldsymbol{\gamma}_t \equiv \boldsymbol{\alpha}^{(1)} + \mathbf{B}\ \mathbf{f}_t$ that is a $K \times 1$ vector. Using $T$ time-dummy variables, $td_t^{(1)}$, ..., $td_t^{(T)}$, we can write the model as:

$$\begin{aligned} \ln d_{mt} &= \alpha_m^{(0)} + \left[\begin{array}{cccc} \mathbf{X}_{mt} * td_t^{(1)}, & \mathbf{X}_{mt} * td_t^{(2)}, & ..., & \mathbf{X}_{mt} * td_t^{(T)} \end{array}\right] \left[\begin{array}{c} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_T \end{array}\right] + u_{mt} \\ &= \alpha_m^{(0)} + \mathbf{X}_{mt}^{*}\ \boldsymbol{\gamma} + u_{mt}, \end{aligned} \tag{A.1}$$

where $\mathbf{X}_{mt}^{*}$ is the row vector $\mathbf{X}_{mt} * [td_t^{(1)}, td_t^{(2)}, ..., td_t^{(T)}]$, and $\boldsymbol{\gamma}$ is the $KT \times 1$ vector with the $\boldsymbol{\gamma}_t$'s. In our estimations the vector $\mathbf{X}_{mt}$ contains $K = 44$ variables at the county level. Therefore, taking into account the interactions with the time dummies, the vector of regressors $\mathbf{X}_{mt}^{*}$ and the vector of parameters $\boldsymbol{\gamma}$ have 499 elements.

*(Step 1) Estimation of vectors of expected LDPB, $\{\boldsymbol{\mu}_t^{D}\}$.* Equation (A.1) is a dynamic linear panel data with fixed effects $\alpha_m^{(0)}$, vector of regressors $\mathbf{X}_{mt}^{*}$, vector of parameters $\boldsymbol{\gamma}$, and transitory shock $u_{mt}$. It is a dynamic model because the vector of regressors includes the lagged dependent variable $\ln(d_{mt-1})$. We estimate the vector of parameters $\boldsymbol{\gamma}$ in this model using two different estimators: a simple fixed-effects (within-groups) estimator, and the Arellano and Bond (1991) GMM estimator. 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. Since the number of periods in our panel

[25] In the model with observable factors, we have used six factors: growth rate of deposits per branch at the national level, growth rate of number of branches at the national level, growth rate of national income, inflation rate, effective Federal Funds rate of interest (annual average), and standard deviation of the weekly average of the effective Federal Funds rate of interest.

is relatively large ($T = 13$), it is arguable that the bias of the fixed effects estimator might not be too large. Arellano-Bond estimator is consistent when $T$ is small, but it may suffer from a weak instruments problem when the coefficient of the lagged dependent variable, $\ln(d_{mt-1})$, is close to one. As a robustness test, we have estimated $\boldsymbol{\gamma}$ using the two estimators, and we have obtained similar results. Given our estimate of the vector $\boldsymbol{\gamma}$, we estimate the fixed effect $\alpha_m^{(0)}$ as $\hat{\alpha}_m^{(0)} = T^{-1}\sum_{t=1}^{T}(\ln d_{mt} - X_{mt}^{*}\,\widehat{\boldsymbol{\gamma}})$. Then, taking into account that $\boldsymbol{\gamma}_t \equiv \boldsymbol{\alpha}^{(1)} + \mathbf{B}\,\mathbf{f}_t$ and $\mathbb{E}(\mathbf{B}\,\mathbf{f}_t) = 0$, our estimator of the vector $\boldsymbol{\alpha}^{(1)}$ is $\widehat{\boldsymbol{\alpha}}^{(1)} = T^{-1}\sum_{t=1}^{T}\widehat{\boldsymbol{\gamma}}_t$. And given $\widehat{\boldsymbol{\alpha}}^{(0)}$ and $\widehat{\boldsymbol{\alpha}}^{(1)}$, the estimated vector of expected 'LDPBs' is $\widehat{\boldsymbol{\mu}}_t^D = \widehat{\boldsymbol{\alpha}}^{(0)} + \mathbf{X}_t\,\widehat{\boldsymbol{\alpha}}^{(1)}$.

*(Step 2) Estimation of variance-covariance matrices of risks,* $\{\boldsymbol{\Omega}_t^D\}$. The estimation of matrix $\boldsymbol{\Omega}_t^D$ has three different parts: (a) estimation of the $K \times K$ matrix $(\mathbf{B}\boldsymbol{\Sigma}_\mathbf{f}\mathbf{B}')$ that accounts for the contribution of 'systematic' risk to the variance $\boldsymbol{\Omega}_t^D$; (b) estimation of the vector of parameters $\boldsymbol{\rho}$ that accounts for additional spatial correlation in local market shocks; and (c) estimation of the parameters $\boldsymbol{\delta}$ that account for heteroskedasticity in variance of diversifiable risk.

*(a) Estimation of matrix* $\mathbf{B}\boldsymbol{\Sigma}_\mathbf{f}\mathbf{B}'$. Define the $K \times 1$ vector $\mathbf{v}_t \equiv \mathbf{B}\ f_t$ associated with the systematic part of the risk. By definition, we have that $\mathbb{E}(\mathbf{v}_t\mathbf{v}_t') = \mathbf{B}\boldsymbol{\Sigma}_\mathbf{f}\mathbf{B}'$. Also, we have that $\boldsymbol{\gamma}_t \equiv \boldsymbol{\alpha}^{(1)} + \mathbf{v}_t$, and therefore, $\mathbb{E}([\boldsymbol{\gamma}_t - \boldsymbol{\alpha}^{(1)}]\ [\boldsymbol{\gamma}_t - \boldsymbol{\alpha}^{(1)}]') = \mathbf{B}\boldsymbol{\Sigma}_\mathbf{f}\mathbf{B}'$. Given our estimators $\widehat{\boldsymbol{\gamma}}_t$ and $\widehat{\boldsymbol{\alpha}}^{(1)} = T^{-1}\sum_{t=1}^{T}\widehat{\boldsymbol{\gamma}}_t$, we have that $T^{-1}\sum_{t=1}^{T}[\widehat{\boldsymbol{\gamma}}_t - \widehat{\boldsymbol{\alpha}}^{(1)}]\ [\widehat{\boldsymbol{\gamma}}_t - \widehat{\boldsymbol{\alpha}}^{(1)}]'$ is a consistent estimator of matrix $\mathbf{B}\boldsymbol{\Sigma}_\mathbf{f}\mathbf{B}'$.

*(b) Estimation of parameters* $\boldsymbol{\rho}$ *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, i.e., $\widehat{u}_{mt} = \ln d_{mt} - \mathbf{X}_{mt}^{*}\ \widehat{\boldsymbol{\gamma}} - \widehat{\alpha}_m^{(0)}$. Given these residuals, we construct the values $\widetilde{\widehat{u}}_{mt}^{(1)}$, $\widetilde{\widehat{u}}_{mt}^{(2)}$, ..., $\widetilde{\widehat{u}}_{mt}^{(S)}$ for the $S$ bands in the spatial autoregressive process of $u_{mt}$. Then, we run an OLS regression of $\widehat{u}_{mt}$ on $\widetilde{\widehat{u}}_{mt}^{(1)}$, $\widetilde{\widehat{u}}_{mt}^{(2)}$, ..., $\widetilde{\widehat{u}}_{mt}^{(S)}$ to obtain consistent estimates of the parameters $\rho_1$, $\rho_2$, and $\rho_S$.

*(c) Estimation of parameters variance of diversifiable risk.* Let $\widehat{e}_{mt}$ be the OLS residuals from the estimation of the spatial process, i.e., $\widehat{e}_{mt} = \widehat{u}_{mt} - \widehat{\rho}_1\ \widetilde{\widehat{u}}_{mt}^{(1)} - \ldots - \widehat{\rho}_S\ \widetilde{\widehat{u}}_{mt}^{(S)}$. 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 (a), (b), and (c), we construct the following estimator of matrix $\boldsymbol{\Omega}_{mt}^D$:

$$\widehat{\boldsymbol{\Omega}_{mt}^D} = \mathbf{X}_{mt}\left(\frac{1}{T}\sum_{t=1}^{T}[\widehat{\boldsymbol{\gamma}}_t - \widehat{\boldsymbol{\alpha}}^{(1)}][\widehat{\boldsymbol{\gamma}}_t - \widehat{\boldsymbol{\alpha}}^{(1)}]'\right)\mathbf{X}_{mt}' + (I - \widehat{\boldsymbol{\rho}}\mathbf{W})^{-1}\ \mathbf{D}(\widehat{\boldsymbol{\delta}}, \mathbf{X}_t)\ (I - (\widehat{\boldsymbol{\rho}}\mathbf{W})')^{-1}. \quad \text{(A.2)}$$

## APPENDIX C: Relationship between liquidity risk and rate of return on equity

This 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 $E_t + D_t = L_t + B_t$, i.e., total liabilities equal total assets. For simplicity suppose that equity $E_t$ and illiquid assets $L_t$ are constant over time, i.e., 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 $L$ in order 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 $\Delta B_t = \Delta D_t$. However, when $\Delta D_t$ is sufficiently negative (i.e., deposit withdrawals are large enough) such that $\Delta D_t < -B_{t-1}$, the bank should sell some of its illiquid assets. Therefore, we can represent a *liquidity shortage* in terms of the condition $\Delta D_t < -B_{t-1}$, or taking into account that $D_{t-1} = B_{t-1} + L - E$, this condition is equivalent to $D_t < L - E$. Suppose that the stochastic process for the bank deposits is $\ln(D_t) = \mu + \sigma\ u_t$, where $\mu$ and $\sigma$ 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 $\sigma$ as a measure of the deposit risk for the bank. Then, the probability of a *liquidity shortage* is $p = \Phi\left(\frac{\ln(L-E)-\mu}{\sigma}\right)$.

This equation shows the relationship between the probability of a liquidity shortage, $p$, the deposit risk, $\sigma$, and the variable $\ln(L-E)$ that is related to the rate of return on equity. If the return to illiquid 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 the illiquid assets. Combining this definition with the previous equation, and given the invertibility of the CDF $\Phi(.)$, we can get the following relationship between $ROE$, $p$, and $\sigma$: $\ln(ROE) = \alpha + \sigma\ \Phi^{-1}(p)$, 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 $\sigma$, i.e., 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.

**APPENDIX D: Efficient Risk-Expected LDPB 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, i.e., $R = f(S)$, 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 $w_1$, $w_2$, ..., $w_M$) 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 paper are not standard. First, in our case the unit of each asset is a branch that is discrete and indivisible, i.e., 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 Riegle Neal Act, 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 LDPB pairs $(S, R)$ such that $R = f(S|G, h, maxn)$ and:

$$\begin{aligned} f(S \mid G, h, maxn) \quad &= \quad \max_{\{n_1, n_2, \ldots, n_M\}} \sum_{m=1}^{M} \left(\frac{n_m}{maxn}\right)\ \mu_m^* \\ &\quad \text{subject to: } n_m = 0 \text{ if } m \notin G;\ n_h > 0;\ \sum_{m=1}^{M} n_m \leq maxn; \\ &\quad \text{and} \quad \sum_{m=1}^{M} \sum_{m'=1}^{M} \left(\frac{n_{im}}{maxn}\right)\left(\frac{n_{im'}}{maxn}\right) \sigma_{mm'}^* = S^2 \end{aligned} \tag{B.1}$$

**APPENDIX E: 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: (1) $ACT$ is the dummy variable that indicates that the CERT is active at year 2006; (2) $ACTMERG$ 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; (3) $MERG$ is the dummy variable indicating that the CERT has been involved in a merger between 1995 and 2006; and (4) $MERGOUT$ 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 Appendix E presents the eight possible values of these variables.[26] 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 multi-state 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 being involved in any merge (i.e., type (D)), or in within-state merger(s) only (i.e., type (E)), or in multi-state merger(s) (i.e., type (F)). Finally, histories (G) and (H) represent banks with $ACTMERG$ equal to 1: 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 multi-state merger(s) (i.e., type (H)).

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

## Table: Appendix E
## Description of Counterfactual Distributions in Figures 12 and 13

| | Bank History 1995-2006 | | | | # banks | Counterfactual Distribution $f(\Omega_{06}, I_{06}^{IN}, n_{06}^{IN})$ | | |
|---|---|---|---|---|---|---|---|---|
| | ACT | ACTMERG | MERG | MERGOUT | (%) | 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 denovo branching outside home state. |
| (E) | 1 | 0 | 1 | 0 | 1,135 (8.0%) | Included | Included | Actual network in 2006 but "closing" branches that come from denovo 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 denovo or mergers. |
| (G) | 0 | 1 | 1 | 0 | 3,897 (27.5%) | Not Included | Not Included | None. Including these banks is redundant with type (E). |
| (H) | 0 | 1 | 1 | 1 | 1,339 (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%) | | | |

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