Geographic Diversification and Bank Stability: Evidence from the 2008-2011 U.S. Banking Crisis

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Abstract

This paper shows that greater bank geographic diversification leads to a sizable decline in bank failure rates. I find that during the 2008-2011 U.S.banking crisis, several measures of bank stability among U.S. banks are sensitive to an exogenous and novel measure of geographic diversification. Alternative explanations including risk-taking, competition, capital reserves or bank size cannot explain this result. Overall, geographic diversification by banks is found to have a substantial and persistent effect on bank stability that is most pronounced for smaller banks. (JEL: G21, 50, D82)

Keywords: bank stability; geographic diversification; branching; banking competition; U.S. banking crisis 2008-2011

The question of how geographic diversification affects bank stability has long been of concern to the literature on bank stability. While recent work largely focuses on the propagation of shocks originating from large banks via counterparty exposures, the great majority of U.S. bank failures during the 2008-2011 U.S. banking crisis occurred among small and mid-sized banks and were due to persistent declines in local real estate and labor markets. These economic shocks could have been mitigated by geographically spreading mortgages and loans (which constitute 76% of bank assets in January 2013) across economic areas that operate on distinct local business cycles.

Since most lending relationships in the U.S. occur within a radius of less than 10 miles (Brevoort and Wolken, 2009), geographically diversifying bank assets implies increasing a bank's geographic footprint: geographic diversification and bank branching thus go hand-in-hand. Branching into new markets however simultaneously leads to an increased exposure to banking competition, which by itself may impact bank stability. Additionally, more efficient and stable banks may choose to geographically expand prior to the crisis; thus banks' inherent strength rather than geographic diversification may account for the observed higher survival rates. Finally, banks may choose to reduce their capital reserves as they increase their degree of diversification thereby deliberately offsetting any declines in risk due to more diversification (Demsetz and Strahan, 1997; Carlson 2004).

To provide convincing empirical evidence that geographic diversification improves bank stability, two hypotheses must be tested. First, that there are sufficient potential diversification benefits available from local geographic diversification. If local economic business cycles were largely synchronized, it would be unlikely that small and mid-sized banks could gain from nearby geographic diversification. Second, that local economic conditions do affect bank stability. If banks made extensive use of financial products that allow geographic diversification independently from one's geographic footprint (e.g., asset backed securities or syndicated loans with creditors spread across different economic areas), local geographic diversification would be unlikely to affect bank stability. I show empirically that both hypotheses hold.

To identify the effect of geographic diversification on bank stability, I make use of exogenous topographic variation (such as oceans and international borders) that impact the availability of distinct U.S. county business cycles nearby bank headquarters. The instrument thereby captures the *potential* of banks to geographically diversify nearby that is due to exogenous variation in topography.

While some banks in midwestern states have plenty of potential counties with diverse local business cycles nearby, banks in Florida for example are surrounded by oceans and banks in Michigan are limited by the Great Lakes, the international border with Canada, and an automotive industry that imposes similar business cycles on nearby counties. Identification thus relies on the exogeneity assumption that the correlations between local business cycles nearby bank headquarters is unrelated to a bank's level of risk-taking, its size or other bank characteristic that may affect bank stability. I empirically assess and find support for this assumption in a series of robustness tests.

In the context of geographic diversification, I also investigate the role of banking competition as a source of bank stability. To do so, I use state-level restrictions on interstate branching before the crisis (1997-2005) and long-before the crisis (1978-1997) to instrument for the amount of competition a bank was exposed to prior to the 2008 U.S. crisis.

The results show that both portfolio diversification and banking competition are positively correlated with bank survival, reducing the probability of failure by 5.8% per standard deviation of portfolio diversification and by 1.6% per standard deviation of banking competition. These are very large effects given an *unconditional* probability of failure during 2008-2011 crisis of 5.2% and are robust to a range of verification tests. The findings on bank survival are confirmed with a number of alternative bank distress measures: the volatility of earnings, the distance from insolvency as captured by bank Z-scores, the proportion of at-risk loans and the length of survival of non-surviving banks. Finally, the degree of geographic diversification is shown to also play a relevant role outside the crisis period, even though its strongest stabilizing impact is experienced during the crisis.

The remainder of the paper is organized as follows. Section 1 provides a brief summary of the 2008-2011 U.S. banking crisis and an overview of related literature. Section 2 introduces the methodology and data while section 3 presents the empirical findings. Section 4 concludes.

1 The 2008-2011 U.S. Banking Crisis

Between 2008 and 2011, the FDIC closed 427 banks as their risk-adjusted capital reserve ratios had fallen below the mandatory 3% threshold.[1] During the same time another 486 banks were taken over by competitors, often during financial distress. As a result, the number of banks dropped between January 2008 and December 2011 by a staggering 913 banks, or 10.6% of the U.S. banks that had existed in January 2008. These numbers compare to a total of just 575 FDIC-closed banks in almost 50 years (11 failures per year) between 1934 (the inception of FDIC deposit insurance) and 1981 (shortly before the start of the Savings & Loan crisis) and just 73 bank failures (or 6 per year) for the 14 years between 1994 and 2007.

If we restrict our attention to only publicly listed banks, we can use the market valuation of banks to learn the investors' view about the severity of the crisis. Figure 1 shows the daily combined market valuation of all publicly listed U.S. banks (solid line) and its standard deviation based on a 3-month rolling window (dashed line) between January 2005 and December 2010. At the height of the crisis the aggregate market valuation of all public U.S. banks had fallen from a peak of $1.72 trillion in February 2007 to a low of $426 billion in March 2009 − a staggering decline of 75.3%. Simultaneously, in a sign of increased uncertainty, the standard deviation of U.S. banks' total market valuation tripled.

[Insert Figure 1 here]

Even though the panic in financial markets had subsided months earlier (cf. Figure 1), among the 506 publicly listed banks that had survived until December 2009, 56 banks still had market valuation declines in excess of 90% and more than half of all the banks (266 banks) continued to have valuation declines in excess of 50%. An additional 135 banks had delisted between 2007-2009.

A major factor that led to a stabilization of the U.S. banking sector was a federal recapitalization program for struggling banks in 2009. By December 31, 2009, the U.S. Government had injected a total of $200 billion as part of TARP's Capital Purchase Program into 704 bank holding companies that owned 742 banks. In 657 (or 90%) of those injections, the government received preferred

[1] Another 50 banks were closed between January 1, 2012 and December 31, 2012.

stocks, thus effectively nationalizing part the U.S. banking sector.[2] By June 2012, 341 institutions had repaid TARP funds, while another 401 banks were still partly owned by the government. Nonetheless, in another sign of persisting bank distress, 921 U.S. banks with combined assets of $349 billion remained on the FDIC's (unofficial) list of "problem banks" as of July 2012.[3] Combining these facts, the 2008-2011 period qualifies as one of the worst banking crises in modern U.S. history.

Notably, 249 out of the 427 bank failures in our sample occurred in 2010 or 2011 – long after the panic of the Lehman failure in September 2008 and many months after the market valuations of public banks had recovered. Owing to a robust intervention by regulators, the majority of 2008-2011 U.S. bank failures had not been triggered by the propagation of a large bank default shock via payment systems or counterparty exposures in the asset markets. Instead – as the next section shows empirically – the majority of U.S. bank failures were due to sharp declines in local real estate and labor markets affecting bank portfolios and performances. These bank failures could have potentially been reduced by a greater degree of geographic diversification of banks' mortgage and loan portfolios.

The idea that greater geographic diversification via bank branching may lead to more bank stability is not novel (e.g., Sprague, 1903). Empirical studies on the Great Depression have also found supportive evidence that U.S. states that allowed for greater bank branching indeed experienced lower bank failure rates (Friedman and Schwartz, 1963; Grossman, 1994; Wheelock, 1995; Calomiris, 2000). Much of the rationale for the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) was further based upon the presumed expected benefits that greater geographic diversification would bring for efficiency and stability (Shiers, 2002). More recently, U.S. regulators have identified the failure to diversify among the major reasons for bank failures in the recent crisis (Fuchs and Bosch, 2009:4).

While greater bank stability at the state-level has generally been attributed to geographic diversification and branching, Calomiris and Mason (2000) and Carlson (2004) analyze individual bank-level

[2]In the remaining 10%, it received subordinated debentures thereby becoming a non-collateralized creditor. (Data based on an analysis of the CPP transaction lists in Office of the Special Inspector General for the Troubled Asset Relief Program (2010: 173-198; 2012: 239-256).

[3]The FDIC does not make its list of problem banks public. Various sources however compile an unofficial list by collecting the publicly available FDIC enforcement letters to banks (consent orders, cease and desist orders, etc.). The reported numbers are based on a list compiled in July 2012 by calculatedriskblog.com.

data during the Great Depression and find the opposite result: branch banks were more likely to fail and tended to fail sooner than unit banks. This, so the authors argue, was due to the lower capital reserves that banks with branches held relative to unit banks. Thus, instead of retaining the lower bank risk attained from diversification, bank managers during the Great Depression sought higher expected returns by lowering capital reserves. Demsetz and Strahan (1997) find a similar conflict between greater diversification and lower capital ratios in a more recent data set: the authors analyze market measures of diversification for 150 publicly listed bank holding companies between 1980 and 1993. While larger bank holding companies have higher measures of diversification than smaller ones, the stocks of both exhibit historically similar risk. The authors explain this inconsistency via greater risk-taking: any diversification benefits that larger banks accrue are offset by lower capital ratios and larger credit risks.

Carlson and Mitchener (2006) suggest an alternative channel to reconcile the two conflicting findings that fewer state branching restrictions lead to more stable state banking systems in the aggregate but also to greater failure rates for branch banks relative to unit banks. The authors argue that branching allows more efficient banks to enter the markets of inefficient banks, thereby purging the banking system (prior to the arrival of a banking crisis) from the weakest and most inefficient banks. While fewer branching restrictions and the ensuing competition may therefore leave the banking system more resilient in the aggregate, it is consistent with the observation that branch banks may fail earlier and more often than unit banks due to lower capital buffers.

Existing empirical work thus suggests that greater geographic diversification may increase overall bank stability through a greater level of diversification of bank portfolios, thereby isolating banks against local economic shocks in labor or real estate markets. The literature however also suggests that those benefits may be offset by banks lowering their capital reserves, thereby increasing their exposure to unforeseen shocks. If this was true, new banking regulation that incentivizes banks to diversify geographically may well be rendered ineffective by bank managers' subsequent decision to reduce capital buffers. Finally, greater geographic diversification also increases a bank's exposure toward banking competition, whose effect on bank stability remains unresolved in the literature.

2 Data and Methodology

2.1 Data

2.1.1 Bank branch networks and branch deposits

I collect all U.S. bank branches with their addresses between 1994 and 2011 from the FDIC's Summary of Deposits database. In total, the data set covers 28,201 distinct depository institutions and a total of 1,597,842 branch-year data points. Table 1 provides summary statistics. Column 1 shows that between 1994 and 2011 the number of banks declined by over 40% from 12,980 to 7,512. At the same time, the total number of branches simultaneously increased by 21 percent from 80,788 to 97,678. As a result, the average (surviving) bank more than doubled the number of its branches from 6.22 to 13.00, corresponding to an average annual growth rate in the number of branches of 4.4 percent. Several spread-related measures of branching also show increases in geographic reach: the mean distance for the average bank between its headquarter and its branches (column 7) increased from 9.31 miles to 25.38 miles and the number of counties the average bank is invested in (column 8) has increased from 1.89 to 3.54. Further, the percentage of institutions that operate branches outside their home state (column 9) increased in the aftermath of the Riegle-Neal Interstate Branching Act from 0.7 percent to 8.7 percent. [4] The percentage of banks that operate branches farther than 100 miles away from their headquarters (column 10) tripled from 4.4 percent in 1994 to 11.2 percent as of 2011 and the number of population living within the average bank's network (column 11) increased by 72% from 950,000 to 1,634,000.

I further collect the amount of deposits obtained from each branch between 1994 to 2011 from the FDIC's Summary of Deposits database. Between 1994 and 2011, total deposits (column 3) increased from 2.82 to 10.46 trillion dollars (in constant 2000 dollar), which corresponds to an annual increase of 8%. Importantly, a steady share of about 70% of deposits are accounted for at local branches rather than at the headquarter (column 5), an interesting finding given an increased prevalence of brokered deposits.[5] Similarly interesting is that deposits account for over 70% of bank liabilities in

[4]Part of this increase is likely due to bank holding companies consolidating their individual institutions in the aftermath of the 1994 Riegle-Neal Act.

[5]Brokered deposits are certificates of deposits that financial institutions can purchase from a broker who pools many small deposits. The price is a fee that is embedded in the interest rate which the purchasing bank needs to pay and which is higher than the one that the broker pays to the ultimate depositors. The counterpart to brokered deposits are core deposits which a bank directly obtains via its branch network from customers. Brokered deposits are typically accounted for at the bank headquarter.

most years (column 6).

[Insert Table 1 here]

2.1.2 Measures of Bank Survival and Bank Distress

As the goal is to analyze bank survival, I use the most direct measure – namely, whether a bank failed or not during the crisis – as the main measure of bank performance/stability during the crisis. Bank failure occurs if a bank is involuntarily closed by the FDIC for falling below the minimum risk-adjusted capital ratio of 3%. Between 2008-2011, the FDIC closed 427 bank. Many banks that did survive the crisis until the end of 2011 may still have experienced significant bank distress or came close to failing. To quantify how close a bank came to failing, I further compute for each bank the minimum capital reserve ratio it attained during the crisis period. While the previous two measures relate to the extensive margin, another measure aims at the intensive margin: for banks that did fail (or were acquired) during the crisis period, I measure the length of survival (in days) between the start of the crisis and the date when they failed (or ceased to exist). Finally, I relate portfolio diversification and competition to traditional book-related measures of bank distress, namely the noncurrent loans to asset ratio, the nonccurent loans to total loans ratio, return on equity, return on assets and a rolling window of the standard deviation of return on assets.

2.1.3 Bank performance data

Besides bank survival measures, I collect bank balance sheet items between 1990 and 2011 from quarterly bank call reports made available in the Statistics on Depository Institutions (SDI) and Uniform Bank Performance Reports (UBPR) databases from the FDIC. Specifically, I obtain items related to firm size (assets, deposits), risk-taking/profitability (return on equity, return on assets, net income, net operating income), investment opportunities (asset growth rate) and bank risk (risk-weighted capital ratio, bank equity, noncurrent loans, and total loans).

2.1.4 County level data on local business cycles and county fundamentals

Further, the measure of portfolio diversification (discussed in detail in 2.2.1) requires local economic performance data. I obtain monthly unemployment levels for all 3,141 U.S. counties from January 1990 to December 2007 from the Bureau of Labor Statistics so to compute the variances and covariances among county business cycles. Finally, to not only consider county business cycles from a labor market perspective, I also collect data on county housing markets. Unfortunately, there is no housing price index available on the county level.[6] A proxy for the county-level can however be obtained from the Building Permits Survey Database of the U.S. Census which provides information on imputed and reported annual construction costs of all new residential housing in a county for the years between 1996-2011.[7]

2.1.5 Banking competition and branching regulation

A well recognized problem in the banking literature is that banking competition cannot be directly measured since often costs and prices for specific bank products are unavailable. While concentration-based measures (such as the Herfindahl-Hirschman index) are widely used in applied work, there is plenty of evidence that concentration-based measures are only very poor proxies of actual competition (see, e.g., Berger, 1995; Bikker and Haaf, 2002). In a cross-country study, Claessens and Laeven (2004) for example find that bank concentration are positively instead of negatively related to competition.

In contrast, several papers use banking regulation that restrict market-entry for competitors as a measure for the degree of banking competition. Claessens, Demirguc-Kunt, and Huizinga (2001) for example analyze how the entry by foreign banks makes domestic banking systems more efficient by reducing profit margins. Barth, Caprio and Levine (2004) investigate the effect from regulatory restrictions across 107 countries and find that more stringent entry restrictions limit competition, determine bank efficiency and impact bank stability. The advantage of such market contestability measures (when available) is that less stringent restrictions are unlikely to decrease competition; thus greater contestability is either increasing competition or has no effect on competition leaving at the very least the directional impact correct.

To side-step the concerns raised over concentration-based competition measures, I collect information from Johnson and Rice (2008) on the evolution of interstate bank regulations after the 1994 Riegle-Neal Act went into effect in 1997. Specifically, while the Riegle-Neal Act removed federal

[6] The two most detailed housing price indices are the Case-Shiller Housing Price Index that reports housing prices for 20 MSAs and the national housing price index by the Federal Housing Finance Agency that is available on the state-level.

[7] A downside of this data source for researchers is that it does not provide an option to download data in bulk, but only separately by state and year. A web-crawling algorithm however is able to download and extract the data.

restrictions that banks could not cross state borders, it provided in a political comprise U.S. states the opportunity to opt out of federal defaults for interstate legislation by creating state restrictions to the entry of out-of-state banks.[8] What followed was a complex web of state level restrictions affecting the ability to establish new and to acquire existing in-state banks by out-of-state banks. Yet another group of states eased restrictions under a reciprocity principle: fewer restrictions applied if the home state of an out-of-state bank likewise provided fewer restrictions. The empirical analysis uses state regulatory changes between 1997 and 2005 and creates a panel of annual pairwise state-to-state regulations along four restrictive dimensions of market contestability.[9] Appendix 2 and section 2.2.2 provide additional details on the data and variable construction.

2.2 Methodology

The main goal is to run the following cross-sectional baseline regression:

$$\begin{aligned}\text{Bank Survival}_{\text{i, crisis}} = \alpha &+ \beta_1 \text{Portfolio Diversification}_{\text{i,pre}} \\ &+ \beta_2 \text{Competition}_{\text{i,pre}} + \gamma X_{\text{i, pre}} + \epsilon_i\end{aligned}$$

where the dependent variable is a measure of bank survival or bank stability during the 2008-2011 U.S. banking crisis. The main independent variables are measures of bank i's pre-crisis level of portfolio diversification and a measure of the degree of competition bank i was exposed to prior to the crisis. The coefficients of interest are thus β_1 and β_2 which provide us with estimates on the benefits from pre-crisis portfolio diversification and banking competition for bank survival during the crisis.

As there is the obvious potential of omitted variables that may be correlated with the key independent variables, the specification is supplemented in a first step with bank covariates as suggested by previous literature to control for pre-crisis bank size (assets, deposits), risk-taking/profitability (return on equity, return on assets, net income, net operating income), bank risk (risk-weighted capital ratio, bank equity) and investment opportunities (asset growth rate). Since there remains the (likely) possibility for endogeneity in this specification, in a second step I make use of two in-

[8] Johnson and Rice (2008) provide an excellent review of the state-wise evolution of branching restrictions after 1997.

[9] In total, the data set consists of 78,400 bilateral restrictions (50x49 states x 8 years x 4 types of restrictions).

struments for the two key independent variables portfolio diversification and banking competition. Specifically, I instrument the *actual* level of portfolio diversification with the *potential* to diversify which depends on geographic characteristics (oceans and international boarders) and the availability of distinct local business cycles in the vicinity of a bank's headquarter. Further, I make use of cross-sectional and time-series variation in interstate branching legislation between 1997 and 2005 and and bilateral state distances to instrument for the amount of competition banks faced in their home state from out-of-state competitors. The next two section provide further details.

2.2.1 Portfolio Diversification

Portfolio diversification is the first key independent variable in our baseline regression. Previous studies use coarse measures of geographic *spread* (for example, an indicator variable whether a bank has branches outside its home county or state) to proxy for the degree of geographic *diversification* of the bank's unobserved portfolio of loans and mortgages. Instead, this measure aims at explicitly incorporating the effect from local business cycle volatility onto bank portfolios, which is desirable for two reasons: first, having branches (and thus mortgages and loans) in several counties does not automatically imply that the assets derived from those counties are uncorrelated with one another as the counties may have very similar characteristics (e.g. same industries or similar rural/urban characteristics) leading to highly correlated business cycles and mortgage and loan portfolios. Hence, the diversification benefit is not guaranteed by distance alone. Second, the most recent crisis has shown that significant differences continue to exist in local business cycles in real estate and labor markets, thus offering a diversification benefit to banks: while a few states saw massive home price depreciations (e.g., Arizona, California, Florida or Nevada), housing prices remained above their 2005 levels in many other U.S. states (e.g., Texas, Washington D.C., North Dakota or Wyoming) throughout the crisis. In fact, as of September 2011, 35 states still had housing prices above their respective 2005 levels and in 10 states housing prices even continued to rise.[10] As a result, the stark decline in the U.S. housing markets should be understood as a regional rather than a national phenomenon. Consequently, geographic diversification – i.e., having physical bank branches in different housing markets – may allow banks to reduce the exposure of their mortgage and loan portfolios to a single market.[11]

[10]Based on monthly FHFA House Price Index data between 2005 and 2011.

[11]To provide a few such examples of housing markets in relative close geographic proximity but on different housing market cycles: while the Pittsburgh MSA saw an increase in its housing prices of 7.9% between January

Besides the housing market, there is also a large variation in local labor market performances across U.S. states and regions. Figure 2 depicts the patchwork of high and low unemployment across U.S. counties – often in close proximity to one another – at the beginning of 2011. Banks located in few counties could thus be more vulnerable to local industry and unemployment shocks while banks with branches in a greater number of counties may benefit through a less volatile deposit base and a higher expected repayment rate of borrowers.

[Insert Figure 2 here]

But how large are the deposit and loan businesses in banks' balance sheets? Are they really large enough to affect a bank's survival? At the end of 2006, the average U.S. bank had 62.4% of its assets in outstanding loans of which 33.8% were in private mortgages, 12.2% in commercial loans and 7.5% in consumer loans. On the liabilities side, deposits made up 70.1% of total fund sources in 2006 while borrowings from other banks or financial institutions constituted only 22.1%.[12] As a result, sources of funds (liabilities) and uses of funds (assets) ought to be sensitive to the local economic conditions in housing prices and unemployment levels, which in turn affect the valuation of assets and the probability of repayment by borrowers. This proposition is empirically tested in section 3.1.

To capture the benefits from geographic diversification our measure relies on basic portfolio theory. Specifically, the variance of a portfolio of n assets is calculated as:

$$\sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\omega_i\omega_j\sigma_{ij} = \sum_{i=1}^{n}\omega_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n}\omega_i\omega_j\sigma_{ij}$$

where ω_i represents the portfolio weight of asset i and σ_i^2 and σ_{ij} are the variance and covariance of the historic payoffs of assets i and j. Assuming that banks obtain deposits and invest into mortgages and loans in those counties where they have a physical bank presence, I consider each county as an asset into which a bank can invest by establishing a bank branch. Hence, a branch

2007 and December 2011, the Cleveland-Elyria-Mentor MSA was down by 18%. Meanwhile, the Detroit area (Warren-Troy-Farmington Hills-MSA) saw an even starker decline of 33%. While the housing prices in the Phoenix-Mesa-Glendale MSA declined by 51%, the Dallas-Plano-Irving MSA had remained unchanged and the Houston-Sugar Land-Baytown MSA was up by 5%. Finally, even though all of California was badly hit by the housing crisis, there is still heterogeneity in its severity: the San Diego-Carlsbad-San Marcos MSA saw a decline of 30%, while the Riverside-San Bernardino-Ontario MSA east of L.A. experienced a 52% decline. (All numbers based on seasonally adjusted purchase-only housing prices available from the Federal Housing Finance Agency for the largest 25 MSAs at `http://www.fhfa.gov/Default.aspx?Page=87`.)

[12] Numbers based on bank call reports.

network becomes a bank's chosen portfolio. I further use the total branch deposits derived from a county as a share of a bank's total deposits as the weight with which the bank is invested into that county. The riskiness of each county (σ_i^2) subsequently depends on the county's local business cycle in its labor market since this represents the local economic conditions that affect a bank's profitability through its lending and deposit businesses. Further, the covariance term σ_{ij} represents the covariance of county i and js' business cycles – a lower covariance thereby implies a larger diversification benefit.

I compute for each bank k the portfolio risk of its loans and mortgages in year t via the variances and covariances of the county business cycles in which bank k has branches as of year t. The lower the portfolio risk, the more diversified is a bank. Specifically, the portfolio risk of bank k in year t is computed as:

$$\sigma_{k,t}^P = \left(\sum_{i=1}^{N_t} \sum_{j=1}^{N_t} 1_{ktij} (\omega_{it} \omega_{jt} \sigma_{ijt}) \right)^{\frac{1}{2}}$$

where

1. $1_{ktij}(\cdot)$ is an indicator function which is 1 if bank k has in year t at least 1 branch in counties i and j.
2. ω_{lt} is the share of deposits that bank k derives in year t from county l relative to its total deposit base.
3. σ_{ijt} is the covariance between the business cycles of counties i and j for year t based on monthly county unemployment numbers between Jan 1990 and Dec of year $t-1$.
4. N_t is the number of U.S. counties that existed in year t (e.g., 3,141 in 2005)

Two facts are worth noting. First, portfolio risk does not simply capture bank size: the correlation coefficient between bank size (measured by bank assets) and portfolio risk is not significantly different from zero.[13] Instead, since banks typically do not expand into far-off regions, a bank's portfolio risk depends in part on the covariances of local business cycles of counties that are close

[13]As a case in point, while Michigan's Citizens Republic Bancorp ranked with \$7.6 billion assets in the top size quintile in 2007, it also ranked in the top quintile of portfolio risk. This may in part be due to the fact that Michigan counties exhibit very similar business cycles and do not offer much potential for diversification (which is discussed more in section 3.4).

to the bank's existing network and which are therefore potential candidates to expand into.

But do business cycles of nearby counties provide sufficient variation such that banks can achieve a meaningful diversification benefit? Figure 3 shows two densities of correlation coefficients of counties' business cycles. The left panel consists of 4,878,126 pair-wise correlation coefficients of all U.S. counties (the upper triangular of the 3,124 x 3,124 variance-covariance matrix) based on counties' monthly unemployment levels between Jan 1990 and Dec 2006. Not surprisingly, most correlation coefficients are positive, but correlation coefficients below 0.5 are not uncommon and 83.9% of coefficients remain below a threshold of 0.75. As any investment into an asset with a correlation coefficient below 1 provides a diversification benefit, banks seem to have many counties to choose from so to diversify their portfolios. The panel on the right shows the density of 515,294 correlation coefficients of only those counties that are within 200 miles distance of one another and which are therefore more likely candidates to expand into for banks located in one of those counties. While counties closer to one another have on average more similar business cycles, still 63.9% of correlation coefficients remain below a threshold of 0.75. Banks thus retain a significant number of counties within a 200 miles radius to choose from so to reap a diversification benefit. Further reducing the distance to just 50 miles shifts the mass of the distribution further to the right, but still leaves 42.6% of correlation coefficients below a threshold of 0.75 (figure available upon request).

[Insert Figure 3 here]

Second, note that a portfolio with n assets has just n variances but $n(n-1)/2$ covariance terms; thus, the greater the number of assets in a portfolio, the greater the contribution of the asset covariances to the portfolio variance. Eventually, as n becomes large, the portfolio variance approximates the weighted average of the covariances of the individual assets. This has very practical consequences for larger banks as not the variance of individual county business cycles matter any longer, but only its correlation with other counties. As a case in point, in 2007, Wells Fargo operated 3,255 branches across 532 U.S. counties. The 532 county variances in its portfolio risk formula are completely dominated by the 141,246 pair-wise county covariance terms.

[Insert Table 2 here]

Table 2 provides an overview of the evolution of the portfolio risk for banks by different geographic spread between 1994 and 2011. Despite an increase in the average bank network size (cf. Table 1), overall portfolio risk has not changed by a large amount: between 1994 and 2011, the portfolio risk for the average U.S. bank (column 2) declined by just 2.4% (or 6.5% of a standard deviation). Not surprisingly, the portfolio risk of unit banks (column 4) has remained constant as a unit bank's portfolio risk in year t is simply the variance of the one county business cycle in which the bank is located estimated from monthly unemployment numbers from 1990 up to December of year $t-1$. Non-unit banks however experienced a decline of 4.4% (or 12.5% of one standard deviation) in portfolio risk (column 6). Separating the banks by the number of counties into which they were invested, we see that the largest improvements occurred among those banks that invested into 3-10 counties with a decline of 3.0% (or 9.0% of a standard deviation). This raises the question why banks do not make greater use of opportunities to geographically diversify? While banks have indeed grown in geographic reach, county business cycles have simultaneously become more synchronized over the years: using 5-year rolling windows of monthly county unemployment levels, the average correlation of business cycles of counties within a 200 miles radius for example increased from 0.433 in 1994 to 0.528 in 2007. Put differently, recalculating the portfolio risk for all banks in 2011 (column 2) while using 1994 business cycle correlations (based on monthly county unemployment data from Jan 1990 to Dec 1993) leads to an average portfolio risk of 1.476 instead of 1.833. Thus – if local U.S. county business cycles had *not* become more synchronized between 1994 and 2011 – this would correspond to a decline in portfolio risk of 19.5% (or a decline of 52% of one standard deviation) instead of the observed 2.4% (or 6.5% of one standard deviation). One could therefore consider the geographic diversification of banks as an attempt to offset an increasing correlation of local business cycles and thus of the underlying loan and mortgage portfolios.

2.2.2 Banking Competition

The final key variable concerns the degree of banking competition a bank was exposed to prior to the crisis. As discussed earlier, similar to Strahan and Rice (2010), I use state restrictions to interstate banking as market contestability measures are considered a preferred measure for banking competition. Specifically, for the first measure "Openness (to Out-of-State Banking Competition in 2007)", I determine for each bank k in 2007 the number of states that have more lenient restrictions to enter k's home state than the federal defaults established by the 1997 IBBEA. Specifically:

$$\text{openness}^k_{\text{i},2007} = \sum_{j=1,j\neq i}^{n} \sum_{m=1}^{4} 1_{ijm_{2007}}$$

where

1. i represents the home state of bank k
2. m_{2007} represents one of the four interstate banking restrictions types in year 2007 (cf. section 2.1.5 and columns 3-6 in Appendix 2)
3. $1_{ijm}(\cdot)$ is an indicator variable which is 1 if state i applies to banks from state j as lenient or more lenient regulation in restriction type m than put forth by the IBBEA federal default, else 0. Specifically:
   (a) 1 if banks from state j can establish *de novo* branches in state i
   (b) 1 if banks from state j are permitted to acquire in-part institutions in state i
   (c) 1 if banks from state j are permitted to acquire banks in state i that hold deposits larger than 30% of state deposits
   (d) 1 if banks from state j are permitted to acquire banks in state i which are younger than 5 years.

The next section discusses the empirical results.

3 Empirical Results

This section discusses the findings to the following main questions:

1. Do local economic fundamentals (still) matter for bank survival? Or has new financial innovation meanwhile allowed banks to economically diversify independently from their geographic footprint? (In the latter case we would not expect to find any diversification benefits from bank branching.)
2. Did geographic diversification/bank branching impact the probability of bank survival during the 2008-2011 U.S. banking crisis? Further, did U.S. banks simultaneously decrease their capital reserves as they increased their level of geographic diversification?

3. If greater branching is indeed correlated to bank survival, is this due to a greater portfolio diversification, due to a greater previous exposure to competition, or both? What are the contributions and relative magnitudes of the two channels?

3.1 Do local fundamentals (still) matter to banks?

Financial innovations since the late 1990s may have allowed banks to economically diversify their portfolios without having to invest into a greater branching network. On the asset side, even small banks can nowadays invest into residential or commercial mortgage-backed securities that consist of mortgages or loans that are either spread across the country or focused on specific regional markets. A large syndicate commercial loan market allows for diversification in industrial loans, and asset-back securities (auto loans, credit card receivables or student loans) allow banks to reduce their exposure to the housing market. On the liabilities side, some banks have attempted to attract greater deposits via online banking rather than by putting down physical branches. Thus, it is not clear from the outset by how much banks are still affected by local economic conditions.

If banks were indeed diversifying away risk incurred on the local level with nationwide investments, we would not expect to find any geographic clustering of bank failures. Hence, the first test aims to provide evidence that bank failures are geographically clustered (and not randomly spread out across the U.S.). An implicit assumption of this test is that failing banks are located in economically depressed areas and that it is this exposure to local conditions which led to their demise. The second test therefore analyzes whether local economic conditions are correlated with the occurrence of bank failures.

3.1.1 Geographic Clustering

Figure 4A shows a map of the lower 48 U.S. states displaying the geographic location of the headquarters of all U.S. banks as of 2007. Figure 4B displays the location of 427 banks that failed between January 2007 and December 2011 as well as an an (underlying) kernel density map with “hot spots” representing a greater number of banks from the overall population of banks in that area. A visual inspection of the geographic pattern of bank failures in Figure 4B suggests geographic clustering. As the density map however shows, many of the failures also occurred in areas with a greater overall number of banks. In other words, a randomly selected set of banks from the bank population may exhibit a similar visual degree of geographic clustering due to the population of banks being clustered itself. I therefore compute a statistic for the degree of geographic clustering among the failed banks and compare it to the same statistic computed for many randomly drawn samples of banks from the population (thus generating an empirical distribution). Appendix 1 provides the details on the methodology to arrive at the geographic clustering statistic. I find that the degree of geographic clustering among failed banks is indeed significantly higher (lying in the outmost tail of the empirical distribution with a p-value less than 0.001) than the clustering among randomly sampled banks, which confirms that the location of banks that fail are not random.

[**Insert Figures 4A and 4B here**]

3.1.2 Failed Bank Locations and Local Economic Effects

The fact that bank failures are geographically clustered implies that something inherent to those geographic locations ought to be related to bank failures. I therefore test whether local economic conditions can explain the pattern of bank failures and bank survivals in the U.S. between January 2008 and August 2012.

I compute two proxies to measure the economic downturn that occurred on the local (county) level:

1. the change in the county unemployment rate between 2008-2011 (relative to the pre-crisis)
2. the change in the county real estate markets between 2008-2011 (relative to the pre-crisis)

Monthly county-level unemployment data is readily available from the U.S. Bureau of Labor statistics. For each bank that existed as of 2007, I compute the average annual unemployment level that the bank faced in all the counties with at least 1 branch between 2006 and 2011 and define the variable `<<labor market decline>>` as the largest increase in the unemployment level that a bank faced in its branch network between 2008-2011 relative to the base year 2006. This measure thus proxies the extent by which the local labor market within a bank's branch network worsened during the crisis relative to pre-crisis levels. While no housing price indicator is available on the county level, county-level data from the U.S. Census Building Permits Survey provides the annual construction costs of all new residential housing in a county. For each bank I construct a variable called `<<real estate market decline>>` which represents the largest average percentage change in real estate construction costs in all the counties in which a bank had branches between 2008-2011 relative to the pre-crisis base years. As the real estate changes for almost all counties are negative, I invert the sign so to make the results in Table 3 easier to read: thus, a value of 0.5 for the variable `<<real estate market decline>>` implies that the real estate construction market declined by 50%.[14]

[Insert Table 3 here]

Columns 1 to 4 of Table 3 show the results of several logistic specifications where the dependent variable is whether a bank failed (i.e., was closed by the FDIC) or not between 2008 and 2011. Reported are marginal effects at the mean and median with z-statistics in square brackets. All variables are winsorized at the 1% level to protect the results from outliers and bank covariates are standardized. I find that the mean and median probability of bank failure significantly increases with a rise in the local unemployment rate and with a decline in the construction activity within a bank's branch network. In columns (3) and (4), after controlling for a number of bank characteristics, a doubling of the unemployment rate in a bank's branch network increases the bank's failure probability at the mean (median) by between 0.9 (1.7) to 1.6 (2.7) percent. Similarly, a decline in real estate activity in a bank's branch network by 100% is associated with an increase in failure probability at the mean (median) by between 7.9 (16.6) to 15.5 (25.7) percentage points. In practical terms, the median bank experienced a 90% increase in its network unemployment level (relative to 2006) and a 78.9% decline in real estate activity, which corresponds for the median bank (after controlling for bank covariates) to a 1.53% increase in the bank failure probability due to the unemployment increase and a 13.1% increase in the failure probability due to the decline in real estate activity.

[14] As an example, consider "ESB Bank" in Pennsylvania: as of 2008, ESB Bank was represented with 23 branches in 4 PA counties: Allegheny, Beaver, Butler and Lawrence County. The highest unemployment levels in those 4 counties during the crisis period (2008-2011) were respectively 7.7%, 8.2%, 7.4% and 9.5% while the 2006 levels were 4.4%, 4.7%, 4.3% and 5.3%. Thus the largest county-level changes in the unemployment rate were respectively 75%, 74%, 72% and 79%. Taking the average of those four changes, we arrive at an average unemployment increase in ESB's bank network of 75.2%. Similarly, the maximum annual real estate construction costs in the pre-crisis period (2003-2006) for Allegheny, Beaver, Butler and Lawrence County were $396.9, $62.8, $192.4, and $27.2 million. The lowest real estate activity during the crisis period (2008-2011) were respectively $248.8, $28.3, $77.6, and $7.3, thus representing changes of -37.3%, -55.0%, -59.7% and -73.1%. Taking the average of those four declines, we arrive at an average real estate decline that ESB faced via its branch network of 56.3%.

Columns 5 to 8 show the results of several Tobit regressions where the dependent variable is the lowest risk-weighted capital reserve ratio a bank attained between 2008-2011. Since the FDIC closes banks that become critically undercapitalized, this measure relates to the channel through which these bank failures occurred and quantifies how close a bank came to failing during the crisis. I use a censured regression framework since capital ratios are non-negative and the FDIC closes a bank when its risk-weighted capital ratio falls below 3%. I find that local labor market declines (but not local real estate declines) are significantly correlated with capital reserve ratio declines. With the median bank facing an unemployment increase within its network by 90%, capital reserves declines on average by between 80 to 113 basis points.

The results suggest that bank failures are indeed geographically clustered and that local county economic conditions are significantly correlated with the probability of bank failure and bank distress. This leads to the conclusion that local economic fundamentals still matter to bank stability and that a geographic diversification of bank portfolios could be an effective strategy for banks to reduce their exposure to local economic shocks.

3.2 Capital Reserves and Geographic Diversification

Demsetz and Strahan (1997) analyze market measures of diversification for 150 publicly listed bank holding companies between 1980 and 1993 and find that larger holding companies have higher levels of diversification but also lower capital ratios and larger credit risks. Similarly, Carlson (2004) find that unit banks during the Great Depression had significantly higher capital ratios than non-unit banks, suggesting that banks with greater geographic diversification may also decrease their capital ratios. Thus, the positive effects on bank stability that greater geographic diversification may bring may well be offset by bank managers' decisions to lower their capital ratios.

To investigate whether such a trade-off existed among U.S. banks prior to the 2008 crisis, I next investigate the correlation between measures of geographic diversification and risk-adjusted capital reserve ratios. The dataset consists of a panel of all 8,127 U.S. banks included in the FIDC's Uniform Bank Performance Reports with data between 2002 and 2011.

[**Insert Table 4 - Panel A here**]

Panel A of Table 4 shows univariate results for a 2002-2011 data panel as well as a pre-crisis 2006 cross-section in which banks are sorted by the number of branches and the number of counties in which they have a branch presence. While unit banks with just 1 branch had in any given year very high risk-adjusted capital reserve ratios of 23.7 percent between 2002-2011, the ratio quickly declines in the number of branches. Likewise, as the number of counties with a bank presence increases, the ratio declines. The average bank with more than 50 branches and with a presence in more than 10 counties has a risk-adjusted capital reserve ratios of just 12.8 percent – about half of that of unit banks. The marginal (frequency-adjusted) averages show the same trend from 20.4 percent to 13.2 percent as the number of counties increase and from 23.7 percent to 12.9 percent as the number of branches increase. The trend is even stronger in the pre-crisis 2006 cross-section where unit banks had on average capital ratios of 34.8 percent which declined to just 11.8 percent for the largest banks in branches and spread.

[**Insert Table 4 - Panel B here**]

Panel B of Table 4 reports the conditional correlation between the following measures of geographic diversification (used in previous literature) and capital ratios:[15]

1. whether a bank has branches outside its home county,
2. whether a bank has branches outside its home state,
3. the log number of branches,
4. the log number of zip codes in which a bank has branches,
5. the log number of counties in which a bank has branches,
6. the average distance between a bank headquarter and its branches, and
7. whether a bank has a branch farther than 100 miles away.

[15] Each of the 35 coefficients shown in Table 4 Panel B is derived from a separate regression where just one geographic diversification measure is included. Each specification includes standard errors that allow for heteroskedasticity with clustering on the state of the bank's headquarter so to allow for the possibility that state banking regulators may encourage different levels of capital ratios. All variables are winsorized at the 1% level to protect the results against outliers.

Column 1 uses a pooled OLS regression with Newey West standard errors to correct for autocorrelation. It regresses capital reserve ratios on measures of geographic diversification while including state and year fixed effects and finds that all measures are negative and highly significantly associated with capital ratios. This indicates that a greater geographic footprint coincides with lower capital reserves. Intra-county banks for example hold on average 5.69% more risk-adjusted capital reserves than do inter-county banks which is roughly consistent with the decline from 20.4% to 15.1% as observed in Panel A. Capital reserve ratios also decline in the number of (log) branches, (log) zip codes and (log) counties a bank is represented in, the average distance between headquarters and branches (in miles) and an indicator variable whether the bank has any branches further than 100 miles from the headquarter.

Column 2 repeats the analysis of column 1 while adding to the state and year fixed effects an extensive set of bank controls;[16] the previous finding however remains unchanged. Column 3 further adds to the set of controls and fixed effects additional bank-specific intercept terms, thereby controlling for any omitted time-invariant bank characteristics. The identification now relies on the differences between capital ratios within banks before versus after they became more geographically diversified. Understandably, the test loses power as (for example) out of the 8,127 banks in the panel only 460 changed their status from an intra-state to an inter-state bank. Nonetheless, most coefficients remain negative and significant indicating that a greater degree of geographic diversification is associated with lower levels of capital reserve ratios. Finally, column 4 uses a first-difference estimator thus making use of the time-series dimension of our data. First differences cancel out any time-invariant observables and omitted constant unobservables and relies only upon the variation from changes in our geographic diversification measures between $t-1$ and t when the variable of interest (here, some measure of geographic diversification) changes. The coefficient on "intercounty bank" for example states that a bank that transitions from an intra-county bank to an inter-county bank on average experiences an (insignificant) 0.24% decline in its capital ratio in that year (relative to banks that do not transition). 4 of the 7 measures remain significantly negative.

Overall, the results in Table 4 indicate that greater geographic diversification coincides with lower risk-adjusted capital reserve ratios. This provides credence to the related findings by Demsetz and

[16]The set of controls include proxies for bank size (assets, deposits), profitability (return on equity, return on assets, net income, net operating income), investment opportunities (asset growth rate) and bank equity.

Strahan (1997) and Carlson (2004) who suggest that bank managers prefer higher returns when faced with the trade-off between keeping a lower risk level obtained from diversification or higher expected returns. Consequently, when incentivized by regulation to geographically diversify, banks may simply lower capital reserves so to return to what it perceives as its private optimal risk level.

3.3 Geographic Diversification and Stability during the 2008-2011 Crisis

Previous literature has found that greater bank branching leads to an improvement in bank survival during a crisis (Wheelock, 1995 and Calomiris, 2000 on the Great Depression; Gart, 1994 on the Savings & Loan crisis). I investigate this question in the context of the 2008-2011 U.S. banking crisis and provide in Table 5 the association between the number of branches (the most common proxy for geographic diversification) and several measures of bank survival.[17]

[Insert Table 5 here]

As before, the results in Table 5 control for 2007 bank characteristics on size, risk-taking, profitability, investment opportunities and banks' main business model (bank types). The findings confirm that a larger number of branches is positively associated with bank survival, even after controlling for the level of pre-crisis capital reserves and deposits. Specifically, on the extensive margin, I find that a greater number of branches decreases the probability of bank failure (column 1) by 2% (3.4%) at the mean (median) and increases (though not significantly) the probability of bank survival (column 3).[18] Given that a bank fails or does not survive, I further find that the length of bank survival (in log days since the start of the crisis) is also positively and significantly associated with the number of branches (columns 2 and 4). A greater number of branches also reduced (although insignificantly) earnings volatility in the crisis period (column 5). Columns 6 to 8 show that a greater number of branches is also positively correlated with a banks average and minimum distance to insolvency (Z-Score) and is also correlated with a smaller decline of Z-Scores during the crisis period.[19] Naturally, these specifications may still suffer from several endogeneity

[17]A log-transformation of the number of branches shields the results from outliers driving the results. The results are qualitatively the same when using the number of bank branches.

[18]A bank is called a survivor if it neither fails nor is acquired by a competitor.

[19]A bank Z-Score (not to be confused with an Altman Z-score) is computed as (ROA + capital reserve ratio)/std dev (ROA) and is typically interpreted as the distance to insolvency. Note that as capital reserves are an endogenous choice to geographic diversification (cf. section 5.1), Z-Scores are an imperfect measure of bank distress for this study and will not be further investigated.

issues which is addressed in the next section.

While the number of branches has been traditionally used as a proxy of geographic bank diversification, it conflates two distinct effects: first, the effect due to a portfolio diversification as banks spread their assets and liabilities over different economic regions that may operate along different local economic business cycles, and second the effect from being exposed to more competitors prior to the crisis, thus having gained efficiency and strength once the crisis arrives.

Table 6 makes a first attempt towards separating both effects. Instead of using the number of branches, we use the portfolio risk measure as introduced in section 2.2.1 that is based on the variances and covariances between county labor markets in which a bank has branches. We further measure the amount of competition banks face via the openness of the bank's home state in 2007 to out-of-state competitors as described in section 2.2.2.

[Insert Table 6 here]

Table 6 shows the marginal effects at the mean (and, for the key variables, at the median) from several logistic regressions in which the dependent variable is whether a bank failed or not between 2008-2011. All specifications use heteroskedastic standard errors that are clustered at the state level to allow for differences in banking regulation enforcement across states, and all variables are winsorized at the 1% level to protect the results from outliers. The results are consistent with the interpretation that an increase in the portfolio risk in 2007 (i.e., a decrease in the degree of portfolio diversification) is positively correlated with bank failure during the banking crisis. Specifically, an increase in the portfolio risk by one standard deviation is correlated with a significant increase in the failure probability at the mean (median) between 1.0 (1.7) percentage points in specification 3 (for all U.S. banks) and 1.6 (2.5) percentage points in specification 4 (only banks with at least 5 branches). The effects are less strong for pre-crisis openness to banking competition: the probability of failure only decreases significantly for banks with at least 5 branches by 0.9% (1.4%) at the mean (median) per standard deviation increase in state openness to competition in 2007. This is consistent with the finding by Carlson and Mitchener (2006) that within-state competition leads to a greater degree of bank stability.

3.4 Results from an Instrumental Variable Approach

An obvious concern with the results in Table 6 is that there might exist some unobserved variables that are correlated to bank failure and the portfolio risk or the amount of competition a bank faced prior to the crisis. For example, greater risk-aversion by bank managers may be correlated to a lower average credit risk *and* a greater degree of portfolio diversification. If risk-aversion was only incompletely controlled for, the coefficient on portfolio risk may therefore capture some of the effect of managerial risk-aversion and be downwards biased.

To make sure that our results are not just the result of such endogeneity, I suggest two instruments that offer exogenous variation. Specifically, I suggest to use the *potential* for portfolio diversification that a bank has nearby its bank headquarter as an instrument for the *actual* degree of portfolio diversification a bank achieves through its branch network. The instrument is based on the well-established observation that banks do not branch into far-flung regions (due to monitoring and marketing costs and less knowledge about far-off borrowers and markets), but typically branch out along the boundaries of their current networks. I therefore estimate for each bank how much portfolio diversification it *could* have achieved in 2007 if it had been represented with equal weight in each of the counties within a 200 miles radius around its headquarter. Specifically, I compute the potential portfolio risk for bank k as:

$$\tilde{\sigma}^P_{k,i} = \left(\sum_{j=1}^{3,141} 1_{kij}(\omega^2 \sigma_{ijt}) \right)^{\frac{1}{2}}$$

where

- i is the county that hosts bank k's headquarter,
- $1_{kij}(\cdot)$ is an indicator function which is 1 if the distance between the geometric centers of counties i and j is 200 miles or less, and
- $\omega = 1/N_k$ where N_k is the number of counties located within 200 miles of county i.

While, for example, Midwestern banks have plenty of potential urban and rural counties within a 200 miles radius that offer a variety of local business cycles to invest into, banks in Southern Florida are surrounded by oceans, banks in Las Vegas are restricted by the desert and banks in

Michigan are limited by the Great Lakes, international borders and an automotive industry that imposes similar business cycles onto nearby counties. As a result, in part due to this geography, banks in Florida, Nevada and Michigan are "stuck" with counties nearby that offer similar business cycles and less potential to diversify. Thus, the identifying assumption is that topographic variation (oceans, deserts and international borders) and the availability of uncorrelated business cycles in the vicinity of banks' headquarters are exogenous to bank failure other than through its impact on the portfolio diversification of banks.

As an example, using a 200 miles radius around Wayne County (Detroit), Dade County (Miami) and Clark County (Las Vegas), the three counties rank among those with the lowest potential diversification options: relative to all other 3,141 U.S. counties, their counties rank in the 5th, 4th and 2nd percentile of the measure of potential geographic diversification. On the other hand, counties in the top 10 percentiles of potential portfolio diversification are frequently located in Northern Texas, Kansas and Nebraska with rural and urban areas, agriculture and manufacturing as well as some oil and gas industries nearby.

Figure 5A shows the actual portfolio risk measure by county (averaged over all banks that have a headquarter in that county) while figure 5B displays the potential portfolio risk measure within a 200 miles radius.[20] First, it becomes evident that the actual degree of diversification and the potential to diversify are correlated with one another (the unconditional correlation for all banks is 0.588) which is a promising sign for an instrument and the first stage regression. Further, the potential to diversify (figure 5B) is low (dark) in most places where we would expect it to be: Florida, and around the Great Lakes, in the North-East as well as in along the West Coast and Nevada. The highest potential for diversification (light shading) is however located in Midwestern counties and East to where the Rocky Mountains form another natural boundary.

[Insert Figure 5A and 5B here]

To instrument for banking competition, I make use of the time-series dimension of interstate branching laws and reciprocity agreements between 1997 and 2005 as well as the distances between states. Specifically, for each state i, I compute for each state pair (i, j) the number of years between 1997

[20]Maps using a 50 or 100 miles radius look very similar and are available upon request.

and 2005 in which banks from state j were granted more lenient interstate branching/banking restrictions by state i. I then add up the years across all states while inversely weighting each state pair by the distance between both states. The latter step incorporates the fact that even lenient branching restrictions may not matter as much for competition if states are very far apart:[21]

$$\text{openness}_{\text{i,1997-2005}} = \sum_{j=1;j\neq i}^{50} \sum_{m=1}^{4} \sum_{y=1997}^{2005} w_{ij} 1_{ijmy}$$

where

- 1_{ijmy} is an indicator variable which is 1 if state i applies for banks from state j in year y more lenient regulation in restriction type m than put forth by the IBBEA federal default (cf. section 4.1.5), else 0.

- w_{ij} is a distance-related integer weight between 1 (highest state-pair distance quintile; farthest) and 5 (lowest state-pair distance quintile; closest) with intermediate weights according to their quintile rank. The distances between state pairs are computed from their nearest border locations to each other.

As in any instrumental variables approach, two concerns are the explanatory power of our instrumental variables to explain bank failures and orthogonality with the dependent variable. To address the first concern, I provide in all IV-based results the first-stage F-tests as well as the Kleibergen-Paap rk Wald test statistic that tests for *weak identification*. Under weak identification, two serious problems arise: first, two-stage least squares estimators incur a finite-sample bias (in the same direction as the ordinary least squares estimator suffers from), and second standard errors become too small and the asymptotic distribution may be decidedly non-normal, undermining reliable hypothesis testing (Stock, Wright and Yogo, 2002). Stock and Yogo (2005) provide a formally derived test (and critical values) about when instruments become too weak and thus unreliable. Under the null hypothesis of the test, the bias of the two-stage least squares estimator is less than a fraction (for example 10% or 15%) of the bias of the ordinary least squares, thus leading to different critical values depending on that fraction and the number of instruments and endogenous variables.[22] All two-stage least squares results are therefore supplemented by the Kleibergen-Paap rk Wald

[21]As an example: As early as 1998, Hawaiian and New Jersey banks were both able to branch *de novo* into and acquire in-part banks in Maryland (banks from Maryland however had to wait until 2001 to receive the same privilege from Hawaii and could still not establish *de novo* branches in New Jersey as of 2005). Clearly, we would expect a greater increase in banking competition in Maryland from New Jersey based banks than from Hawaiian banks.

[22]See for example Murray (2006) for details.

test-statistic and the applicable Stock-Yogo critical values. Further, I provide in all IV results the p-value of the Kleibergen-Paap rk LM statistic which tests whether the equation is *underidentified*, i.e. whether the instruments are sufficiently correlated with the endogenous regressors to be relevant. Under the null hypothesis, the equation is underidentified so that a small p-value rejects underidentification (cf. Bazzi and Clemens, 2013: 165-175).

The common approach for testing the *orthogonality assumption* of instruments is with the help of the Hansen J-test, which has the joint null hypothesis that the instruments are uncorrelated with the error terms and are therefore correctly excluded from the second-stage estimation. Hansen's J-test however requires over-identification, i.e. more instruments than endogenous variables. I therefore add two additional instruments that I subsequently include into the 2SLS results in order to test the orthogonality assumption. Since the two additional instruments are weaker than the main instruments (as shown in table 7), I do not interpret the results from the coefficients when using the weaker instruments (since they may suffer from a finite sample bias and may have too small standard errors) but only use them so to verify the orthogonality assumption. Specifically, as a second instrument for the degree of banking competition in 2007, I use pre-Riegle Neal state-level interstate branching restrictions between 1978 and 1997: the years before 1997 since a state had entered into an agreement with at least one more state to allow out-of-state banks to acquire in-state banks (cf. column(1) in Appendix 2). As a second instrument for portfolio diversification (or the potential thereof) I use the proportion of land under U.S. jurisdiction within a 200 miles radius around a bank's headquarter.[23] All IV specifications with over-identification thus report the Hansen J-test statistic and its p-value.

Finally, Chernozhukov and Hansen (2008) illustrate that inferences based on reduced-form IV regressions in ordinary least squares with weak instruments can easily be adjusted for heteroskedasticity, autocorrelation and clustering using standard robust covariance matrix estimators so to provide accurate standard errors. As a result, I also provide results from a reduced-form IV regression where the first stage is omitted and the instruments are directly plugged into the second stage regression.

[Insert Table 7 here]

[23]This differs decidedly from the main instrument of portfolio diversification which incorporates the variation in nearby business cycles.

Table 7 provides the results of two-staged least squares regressions and reduced-form IV specifications where the outcome variable is whether a bank failed during the crisis. All specifications use heteroskedastic standard errors with clustering at the state level. Column 1 shows the main specification where actual geographic diversification is instrumented with potential geographic diversification and openness to banking competition in 2007 is instrumented with a bank's home state's openness to competition between 1997 and 2005. The results are qualitatively consistent with those found in Table 6, but the effects have strengthened: a one standard deviation increase in portfolio risk increases the probability of failure by 5.8% while a one standard deviation increase in openness to competition decreases the failure probability by 1.6%. The F-statistics of the first stages and the Kleibergen-Paap statistics are well above the critical values (a value of 10 for the first-stage F-statistics and 7.03 for the Kleibergen-Paap statistics, cf. Stock and Yogo (2005)). Among the bank covariates, more aggressive asset growth rates prior to the crisis increased the probability of failure while more equity and more capital reserves significantly decreased the failure probability.

Columns 2 and 3 introduce the secondary instruments, the proportion of land nearby the bank headquarter under U.S. jurisdiction and interstate branching restrictions between 1978 and 1997. Not surprisingly, the first stages are significantly worse (and, for the instrument on the proportion of bankable land with such a low first-stage F-statistic that drawing inferences from the coefficient becomes unreliable). The sole purpose of including these inferior instruments is to achieve over-identification in specifications 4-7 so that the Hansen J-test statistic can be obtained.[24] In specifications 4-7, I subsequently use combinations of the four instruments and obtain the corresponding Hansen J-test statistics. While weak identification continues to be soundly rejected by the Kleibergen-Paap statistics, the Hansen J-statistics have p-values of 0.58 or higher, i.e. the test cannot reject that the instruments are indeed orthogonal to bank failures. Specification 7 further excludes banks that have less than 5 branches as of 2007 and finds a further strengthening of the portfolio risk and competition effect on bank failures.

[24]Note that the joint null hypothesis of Hansen's J-test is that all instruments are uncorrelated with the error terms; adding a weak and valid instrument does not adversely impact the inference of the Hansen's J-test for the other instruments. Adding a weak or invalid instrument works against the null hypothesis and makes the rejection of orthogonality more likely.

Finally, following Chernozhukov and Hansen (2008), specifications 8-10 employ a reduced-form IV approach, in which I directly regress bank failure on the two instrumental variables in a single stage (while maintaining heteroskedastic standard errors that are clustered on the state level). The results are consistent with the previous findings: an increase in portfolio risk increased the probability of failure, while greater pre-crisis competition decreased the failure probability.[25] As a result, the findings thus far suggest that both portfolio diversification and banking competition increased bank stability. Further the effect from geographic diversification seems significantly larger than the effect of banking competition.

[**Insert Table 8A here**]

Tables 8A and 8B replaces the dependent variable with alternative measures of bank distress. Columns 1-4 of table 8A analyze the minimum risk-weighted capital ratio that a bank obtained during the crisis period 2008-2011. As the FDIC closes banks that fall below 3% of capital ratio, the decline in a bank's capital ratio is the channel through which failure occurs; it can further be understood as a measure as to how close a bank came to failing. Since capital ratios are non-negative, specifications 1 and 2 employ a Tobit specification with a lower bound of 0 while specifications 3 and 4 use two indicator variables whether a bank failed or had capital reserves below 3% at any point in time. Specification 1 employs the actual portfolio risk in 2007 and openness to banking competition as of 2007 as the two key independent variables and finds that a higher portfolio risk leads to a lower capital ratio (and thus an increase in bank distress) during the crisis. Greater pre-crisis competition however does not significantly impact capital ratios during the crisis. Specifications 2-4 revert to the main instruments, first in a reduced-form Tobit framework, and then in a two-stage least squares framework. The findings confirm those from specification 1: the minimum capital reserve ratio levels during the crisis are negatively correlated to the potential to diversify by between 68 and 71 basis points for all banks and 39 basis points for banks with at least 10 branches. Pre-crisis openness to competition however does again not affect the capital reserve ratios during the crisis.

Specifications 5-9 repeat the analysis by investigating how the length of survival during the crisis for non-surviving banks (banks that failed or were acquired by competitors) relates to pre-crisis

[25] Results from reduced-form IV logistic regressions are very similar and available upon request.

portfolio risk and competition levels. The Tobit specifications in columns 5 and 6 includes upper and lower bounds for 0 days and 1,643 days (surviving until the end of 2011) while the 2SLS specifications in columns 7 and 8 include indicator variables whether a bank failed within 50 days or fewer or survived more than 1,600 days. To make sure that outliers do not drive the results, column 8 employs a log-transformation of the dependent variable. The findings in columns 5 to 8 are consistent with the notion that a higher pre-crisis portfolio risk decreased the length of survival while a higher level of pre-crisis openness to competition increased the length of survival. Larger banks and banks with more aggressive asset growth rates pre-crisis survived a shorter time periods, while those banks with more equity, more deposits and higher pre-crisis capital ratios survived longer. While the exact effect of portfolio risk and competition varies across the Tobit and 2SLS specifications, the signs are consistent with those found in previous tests and confirm the benefits of banking competition and portfolio diversification on bank stability.

[**Insert Table 8B here**]

Table 8B repeats the exercise with three alternative book-based measures of bank stability: the standard deviation of return on assets as a measure of earnings volatility during the crisis, the ratio of noncurrent loans relative to assets, and the noncurrent loans to total loans ratio. Specifications 1, 4 and 7 use the actual portfolio diversification and openness of home states to competition as of 2007 while the remainder specifications employ the instruments. The results are in line with those of earlier tables: a higher portfolio risk pre-crisis led to greater earnings volatility and noncurrent loan ratios during the crisis, while more competition in the pre-crisis period negatively affects earnings volatility and at-risk loans.

[**Insert Table 9 here**]

A concern with the previous results might be that some of the banks with greater geographic diversification may also benefit from a too-big-to-fail (TBTF) status which may yet be incompletely controlled for by bank assets and bank deposits. This TBTF-designation in turn may (through various channels) have decreased the probability of failure and thus leads to an upwards bias in the portfolio risk coefficient. Columns 1 and 2 of Table 9 address this concern. In column 1, an indicator variable specifies whether or not a bank was included into the TARP program. The key coefficients remain unchanged. Column 2 further adds several bank spread controls: an indicator variable whether a bank had a branch network crossing a state border, an indicator variable whether it had branches in excess of 100 miles from the headquarter, the log number of branches, the number of counties with a bank branch and the average distance between the headquarter and its branches. Again, the key coefficients on portfolio risk and openness to competition remain unchanged.[26]

Another concern with the geographic risk instrument may be that real estate business cycles nearby natural boundaries (oceans or mountains) may be exacerbated by the lack of land supply for real estate development (Saiz, 2010; Mian and Sufi, 2011). If this was indeed the case, and if risk-seeking (risk-averse) bank managers were to endogenously locate their bank headquarters nearby (away from) such banking markets this would violate our exclusion restriction. Subsequently, as those market also provide fewer opportunities for diversification, this may lead to an upward bias in the portfolio risk coefficient. Before addressing this concern, it is important to realize that the potential to diversify depends on the availability of uncorrelated (labor market) county business cycles nearby. While topographic restrictions impacts this availability, a locally dominating industry may do so likewise. To rule out that the results are driven by topography alone, columns 3 to 6 employ different geographic modifications to our main specification. Column 3 excludes all banks with headquarters in states that have an ocean coastline ("salt-water states"); column 4 further excludes banks with headquarters in Michigan, Ohio and Wisconsin (states bordering the Great Lakes; "sweet- or salt-water states"). The test thus relies on the variation in diversification potential that stems from the diversity of nearby business cycles rather than those from topographic restrictions due to water bodies. While the point estimate on portfolio risk drops from 6.3 to 4.5 percent points, it is not significantly different from the coefficients in specification 2. In column 5, I further exclude all those banks that have less than 90% of their area within a 200 miles radius around their headquarters being "bankable" (i.e., it is neither water nor non-U.S. territory), effectively excluding all banks within a 200 miles band stretching along the coastlines of the Oceans, Great Lakes, and the U.S. international borders with Canada and Mexico. Column 6 recreates a measure similar to the one by Saiz (2010): I compute for each bank the average slope and standard deviation of slopes of all the land within a 50 miles radius around each headquarter.[27] Column 6

[26] Using alternative bank spread measures does not change the results.

[27] Slopes are computed from 30 arc-seconds digital elevation data obtained from the U.S. Geological Survey.

then excludes all banks whose 50 miles area has an average slope that is in the top quartile of all banks' average slope.[28] The goal is thus to exclude those banks that may suffer from greater real estate business cycles due to a considerable constraint on developable land nearby (as argued by Saiz, 2010). The coefficient on portfolio risk declines to 5.0 and 4.2 percent respectively, but again are not significantly different from earlier results. The results of columns 3-6 show that the portfolio risk coefficient is not exclusively driven by topography, but that the availability of local business cycles nearby is likewise important. This in turn raises a new question: Could the result be driven by new banks choosing strategically their headquarter locations to be in areas with many distinct local business cycles nearby? In other words, might headquarter location choice be endogenous? To address this concern, column 7 excludes all banks that were established after 1978, while column 8 only retains banks that were established before 1934. In both cases, it is unlikely that bank managers could have predicted the degree of local business cycle integration 30 and 70 years into the future. The results remain robust to these exclusions.

3.5 Geographic Diversification outside the Crisis Period

Does geographic diversification also matter outside the extreme events of the 2008-2011 banking crisis? To investigate this further, Table 10 shows the unconditional correlation coefficient between a measure of earnings volatility – the standard deviation of return of assets based on a rolling 4-quarter window – and geographic diversification between 1994 (the earliest available year in the FDIC database) and 2011. While the actual portfolio risk is not significantly differently from zero between 1994 and 2007 – a time of relative calm with on average just 6 bank failures per year – it becomes positive and highly significant during 2008 to 2011. As actual portfolio risk may be endogenous, column 2 shows the correlation between earnings volatility and potential portfolio risk (based on a 200 miles radius around a bank's headquarter). This time, the coefficient is positive and significant in all specifications, but particularly so in the 2008-2011 crisis period, indicating that a higher degree of geographic diversification is positively correlated with a lower degree of earnings volatility also outside the crisis period.

[Insert Table 10 here]

[28] An alternative test using the standard deviation of slopes instead of the average slope yields very similar results.

Figure 6 further splits the 2004-2011 period into a pre-crisis period (2004-2007) and a crisis period (2008-2011) and displays the noncurrent loans-to-assets ratio, the noncurrent loans-to-loans ratio, and return on assets by the quintile of portfolio risk. While the bank performance measures across the quintiles do not significantly differ from one another in the pre-crisis period, there is a clear trend towards increasing at-risk loan ratios and lower ROAs the higher the portfolio risk during the crisis period. The fact that bank performance seems little affected by geographic diversification in the pre-crisis period, but is very much so in the crisis period highlights that geographic diversification has its strongest effect still during the banking crisis.

[Insert Figure 6 here]

4 Conclusions

This paper sought to answer three questions:

1. Do local economic fundamentals still matter for bank stability? Or has new financial innovation allowed banks to economically diversify independently from their geographic footprint?

2. Did geographic diversification and bank branching impact the probability of bank survival during the 2008-2011 U.S. banking crisis? Moreover, did U.S. banks decrease their capital reserves simultaneously as they increased their degree of geographic diversification?

3. Finally, is greater bank stability due to portfolio diversification or due to pre-crisis exposure to banking competition? What are the relative magnitudes of the two effects to one another?

These questions are policy relevant to bank regulators who are currently in the process of creating new regulation that aim at insulating bank portfolios from macroeconomic shocks; they receive added urgency as the great majority of recent bank failures were due to local economic fundamentals in local real estate and labor markets. Further, the findings contribute to the literature that investigate whether banking competition increases or decreases bank stability during a crisis and makes a contribution by introducing a novel measure of portfolio diversification that incorporates the volatility and correlations between local business cycles in the economic areas where banks keep their loan and mortgage portfolios.

In regard to the first question, I find that bank failures during the 2008-2011 U.S. banking crisis exhibit statistically significant geographical clustering and that banks that failed were located within counties that were particularly hard hit in their real estate and labor markets. This confirms that the large majority of bank failures between 2008-2011 occurred not due to contagion or systemic risk but due to credit risk in banks' local mortgage and loan portfolios. Local economic fundamentals thus still matter for banks, giving credence to the rationale that banks ought to geographically diversify to reduce their exposure to local economic shocks.

Turning to the second question, theory predicts that greater geographic diversification allows banks to mitigate potentially adverse effects from local business cycles in real estate and labor markets. Several empirical studies however raise doubts that bank stability increases with geographic diversification, suggesting instead that banks reduce capital reserves and increase credit risk as they diversify geographically, and thus becoming more likely to fail during a crisis (Demsetz and Strahan, 1997; Carlson, 2004). I therefore investigate first if U.S. banks reduced their capital reserve ratios as they diversified geographically pre-crisis, and second whether greater geographic diversification increased bank stability during the banking crisis. I find strong evidence for both cases. As the average bank increases its number of branches (or, alternatively, the number of counties it is represented in) its risk-adjusted capital ratio declines significantly. In 2006, the average unit bank had a three times higher risk-adjusted capital reserve ratio (34.8%) than the average bank that had more than 50 branches spread across more than 10 counties (11.8%). The decline in capital reserves is significant and robust to using different measures of geographic diversification and across several regression specifications using bank fixed effects and first differences while controlling for a large set of bank characteristics, state and year fixed effects.

I further find evidence on the extensive margin that greater geographic diversification (as measured by the log number of branches) prior to the banking crisis decreased the probability of bank failure and increased the probability of bank survival (i.e., neither failed nor were acquired). Furthermore, among those banks that did fail or did not survive (the intensive margin), a larger number of branches is correlated with longer survival. I find similar results for measures of earnings volatility and bank Z-Scores. While those findings are consistent with previous results from the Great

Depression and the Savings & Loan crisis, it is not clear whether this increase in bank stability is due to greater banking competition (which forced inefficient banks to exit earlier) or due to a portfolio diversification effect. I therefore use two exogenous sources of variation to disentangle both effects: (1) bilateral state restrictions on interstate banking between 1997 and 2005 (post Riegle-Neal; inversely weighted by distance) to instrument for the amount of out-of-state competition a bank was exposed to in the 10 years prior to the start of the crisis, and (2) topographic variation and the availability of distinct local business cycles nearby bank headquarters that impact the potential for portfolio diversification nearby as an instrument for actual portfolio diversification. I find that both banking competition and portfolio diversification are positively related to bank stability, reducing the probability of failure (while controlling for other bank characteristics including capital reserve ratios) by 5.8% per standard deviation of portfolio diversification and by 1.6% per standard deviation increase in out-of-state banking competition. These are very large effects given an unconditional probability of failure during 2008-2011 of 5.2%. The results are confirmed with alternative bank distress measures, namely (1) the minimum capital reserve ratio a bank attained between 2008-2011 as a measure as to how close a bank came to failing, (2) the length of survival during crisis for non-surviving banks, (3) the standard deviation of return on assets as a measure of earnings volatility, and (4) the proportions of noncurrent loans relative to total assets and total loans. Per standard deviation of portfolio diversification, minimum capital reserve ratios during the crisis are on average higher by 23-71 basis points and the length of survival among non-survivors increases by 79-151 days. While pre-crisis competition does not significantly affect minimal capital reserve ratios, it does increase the length of survival of non-survivors by 33 to 57 days per standard deviation of openness to competition.

Overall, the results suggest that both portfolio diversification and banking competition were beneficial to bank stability during the recent U.S. banking crisis. Further, the contribution from portfolio diversification to bank stability seems to be at least as high, but probably significantly larger than the contribution from banking competition. With just 8.7% of U.S. banks having branch networks that cross state lines, this calls for renewed attention of banking regulators towards branching restrictions, branching decisions and portfolio diversification.

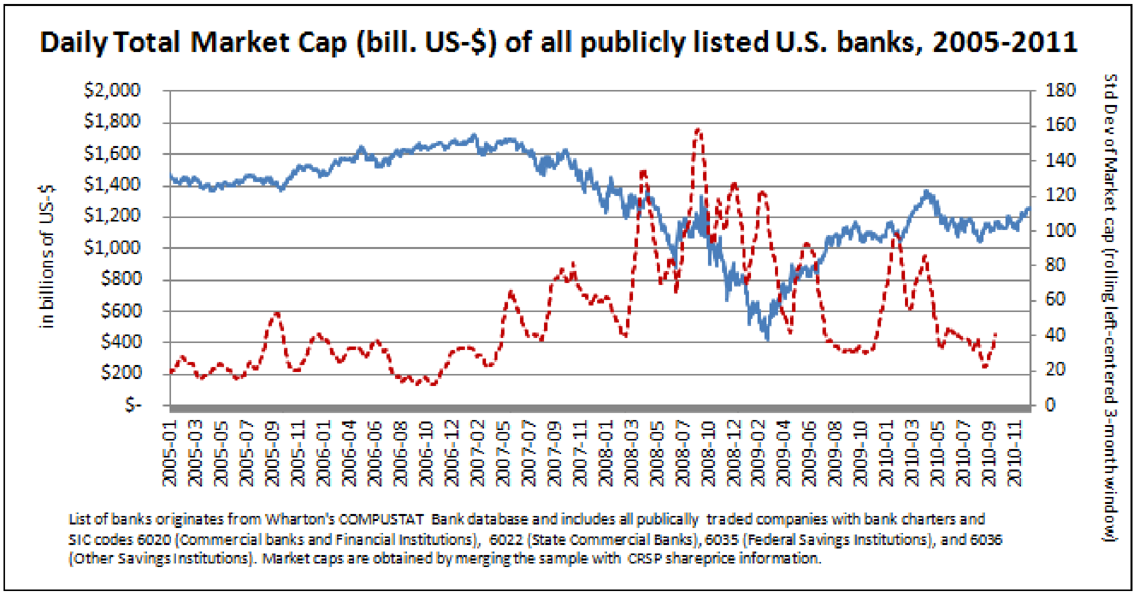


Figure 1: Aggregate Market Capitalization of publicly listed U.S. Banks, 2005-2011

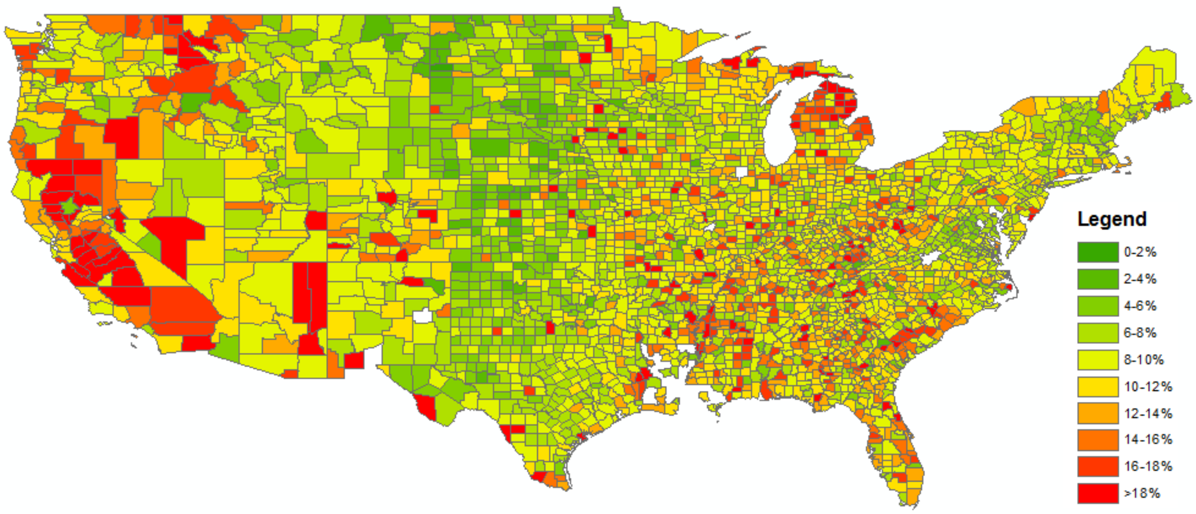


Figure 2: Unemployment Level by County (January 2011)

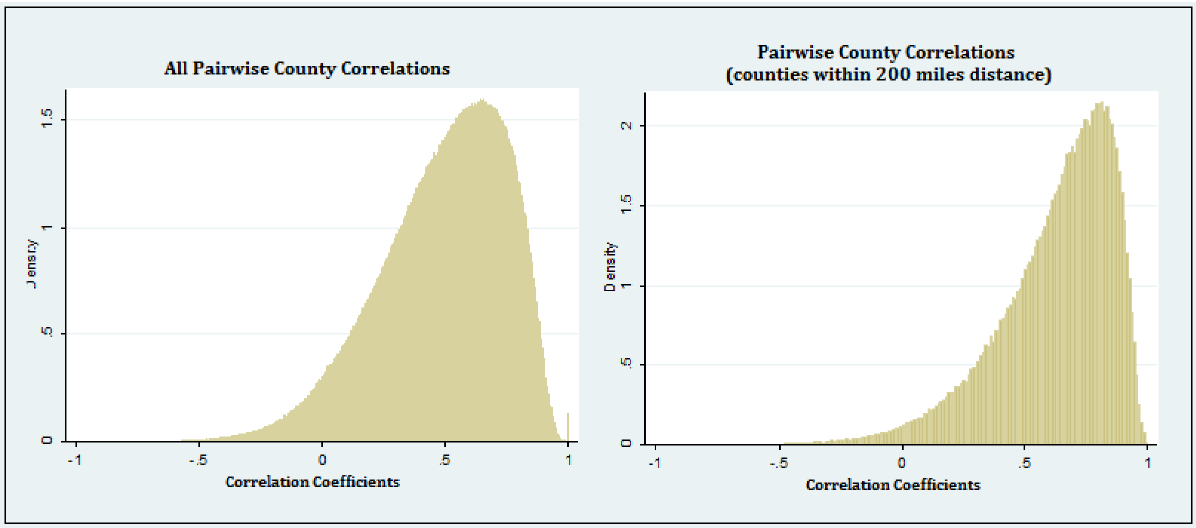


Figure 3: Correlations between Local Business Cycles

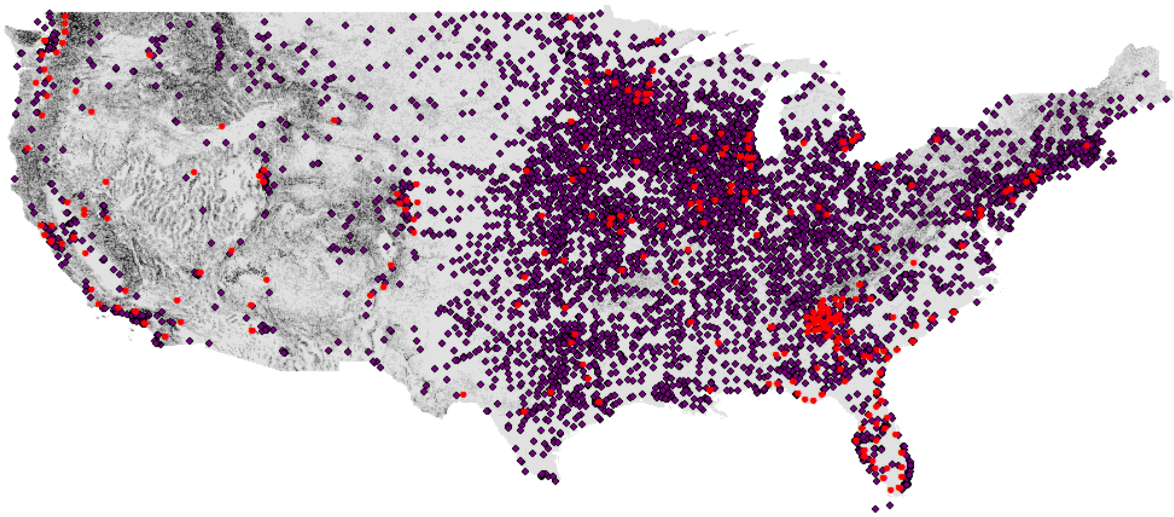


Figure 4A: Map of U.S. Bank Locations in 2007 and Bank Failures 2008-2011

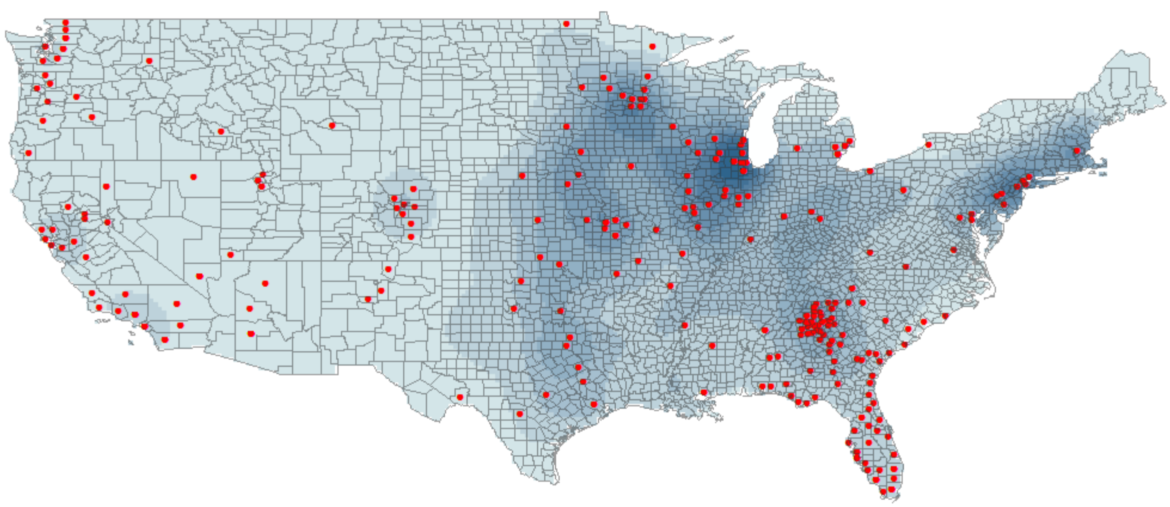


Figure 4B: Map of U.S. Bank Failures (2008-2011) and Density Map of Surviving Banks

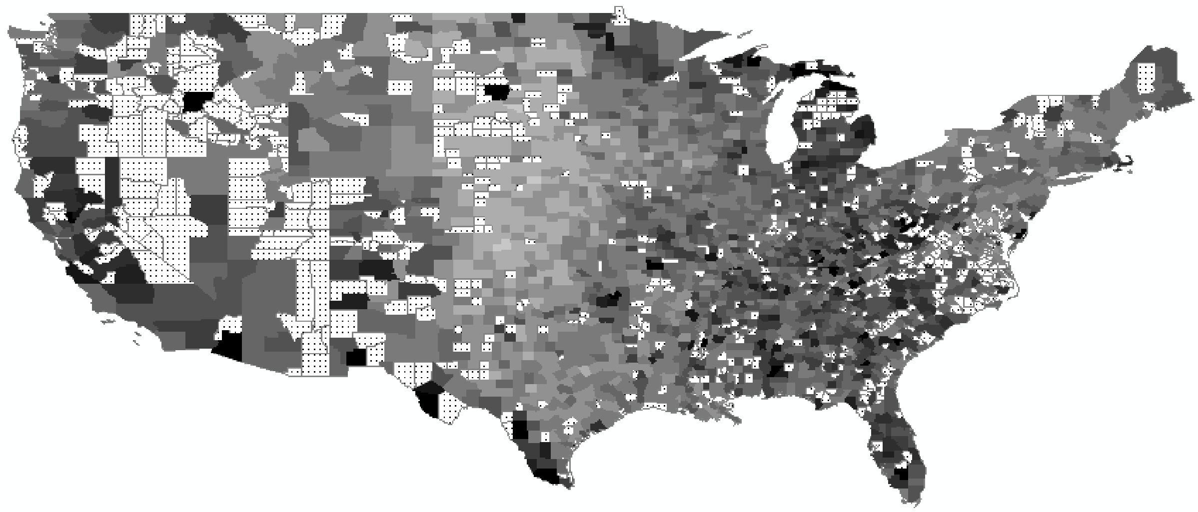


Figure 5A: **Actual** average Portfolio Risk of Banks with Headquarters in a given U.S. county

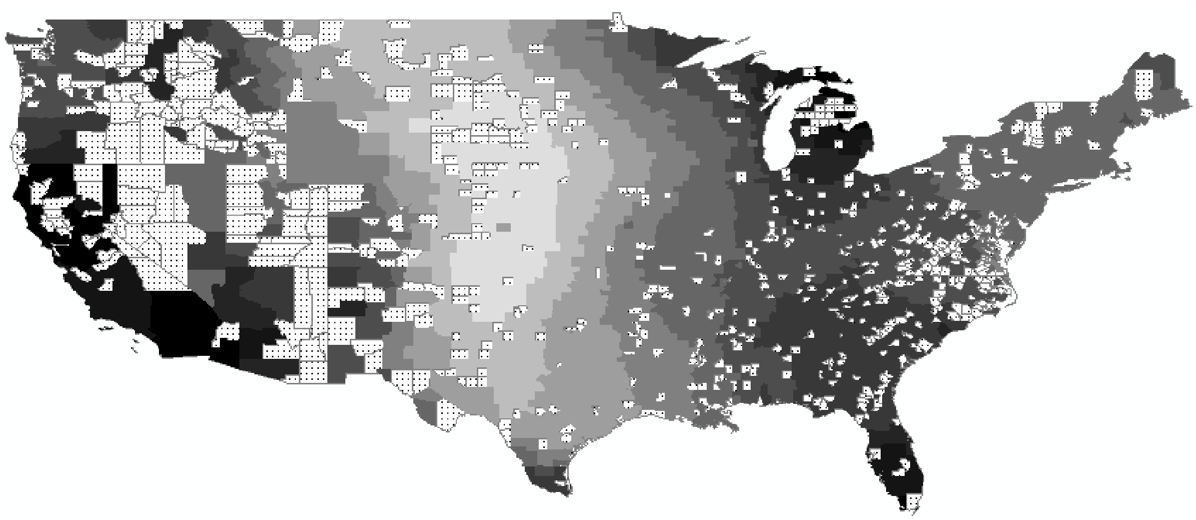


Figure 5B: **Potential** average Portfolio Risk of Banks with Headquarters in a given U.S. county

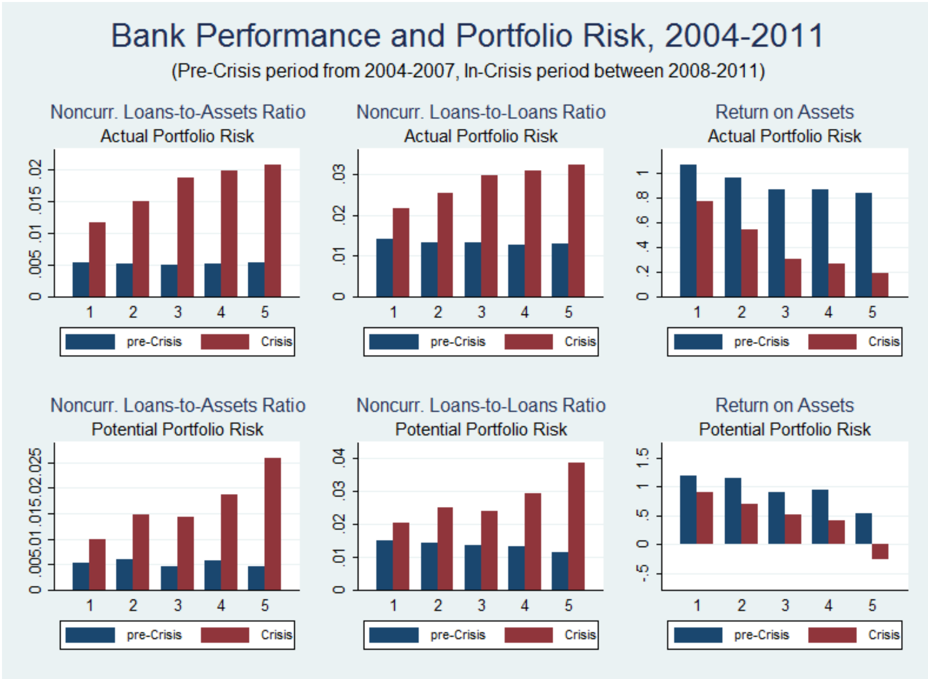


Figure 6: Bank Performance and Portfolio Risk, 2004-2011

Table 1: Summary Statistics

Table 1 shows summary statistics and trends over the sample period on several of the key measures used in this study. Columns (1) and (2) show the number of banks (with unique FDIC certificates) and the number of physical bank branch locations. Column (3) shows the total deposits in banks in trillion $ across all banks and branches (in 2000 constant dollars). As brokered deposits have become more prevalent in recent years, we exclude the HQ at which brokered deposits are usually accounted for in column (4) and provide the ratio of deposits held in branches relative to total deposits in column (5). Columns (7) to (9) show the average distance between branches and bank headquarters in miles, the number of counties the average bank is represented in and the percentage of banks that have branches outside of their home state. Columns (10) and (11) show the percentage of banks that have bank branches farther than 100 miles and the market size (as measured by the population in those counties that a bank is represented in) of the average bank. Column (12) gives the portfolio risk from local business cycles that the average bank is exposed to via its bank branch network. Finally, columns (13) to (16) provide the number of bank failures and the annual number of banks entering and leaving the TARP bailout program. Data sources: Columns (1) and (2) originate from FDIC's institutions directory, columns (3) to (6) from the FDIC's Summary of Deposits Database. Columns (7) to (10) are computed by the author using bank branch data address data from the FDIC's institutions directory. County population data used in columns (11) is obtained from the FRED database of the St. Louis Federal Reserve. Column (16) is based on the failed banks list of the FDIC and columns (17) to (19) from the July 2012 Quarterly Report to Congress by the Office of the Special Inspector General for TARP (Appendix D, pp.239-258).

Year	**Banks**	**Branches**	**Branch Deposits**				**Diversification Measures**						**Bank Distress Measures**			
			All (trill.)	Excl. HQ (trill.)	Branches in %	Deposits as % of total	Avg. Distance	No. of counties	% inter-state	% dist. > 100 miles	Avg. Popul. in net-work	Portfolio Risk	Failure	Joined TARP	Left TARP	Under TARP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1994	12,980	80,788	2.82	1.89	67.10%	78.70%	9.31	1.89	0.70%	4.40%	950	1.878	15	-	-	-
1995	12,266	80,473	2.93	2.00	68.30%	77.10%	9.90	1.96	0.80%	4.70%	957	1.872	8	-	-	-
1996	11,671	80,827	3.09	2.14	69.40%	76.90%	10.79	2.05	1.30%	5.00%	957	1.869	6	-	-	-
1997	11,168	81,541	3.31	2.30	69.50%	75.40%	11.31	2.15	1.90%	5.00%	979	1.865	1	-	-	-
1998	10,719	82,722	3.50	2.48	70.80%	74.10%	12.12	2.25	2.50%	5.30%	1,026	1.860	3	-	-	-
1999	10,328	83,703	3.67	2.60	70.90%	72.40%	13.39	2.36	3.00%	5.80%	1,085	1.858	8	-	-	-
2000	10,100	84,871	3.97	2.82	71.00%	70.50%	14.76	2.45	3.60%	6.20%	1,131	1.860	7	-	-	-
2001	9,739	85,440	4.39	3.07	69.90%	71.20%	15.89	2.56	4.10%	6.60%	1,183	1.857	4	-	-	-
2002	9,456	85,951	4.74	3.34	70.40%	71.50%	16.78	2.63	4.40%	7.00%	1,201	1.857	11	-	-	-
2003	9,242	87,151	5.40	3.81	70.50%	72.00%	17.75	2.71	4.90%	7.40%	1,234	1.855	3	-	-	-
2004	9,050	89,152	5.91	4.15	70.10%	71.10%	18.06	2.78	5.30%	7.60%	1,277	1.855	4	-	-	-
2005	8,840	91,407	6.63	4.81	72.60%	70.30%	19.07	2.90	5.90%	8.10%	1,321	1.851	0	-	-	-
2006	8,750	94,091	7.43	5.34	71.80%	70.10%	20.05	3.00	6.40%	8.80%	1,382	1.849	0	-	-	-
2007	8,588	96,624	7.95	5.81	73.00%	69.70%	21.62	3.12	7.10%	9.20%	1,456	1.851	3	-	-	-
2008	8,425	98,528	8.52	6.14	72.10%	67.80%	22.75	3.23	7.50%	9.90%	1,521	1.849	30	265	0	265
2009	8,169	98,943	9.25	6.73	72.80%	70.90%	23.56	3.33	7.80%	10.40%	1,571	1.845	148	576	70	841
2010	7,809	97,952	9.53	6.93	72.70%	72.60%	23.85	3.43	8.10%	10.70%	1,570	1.838	157	-	103	771
2011	7,512	97,678	10.46	7.46	71.30%	74.30%	25.38	3.54	8.70%	11.20%	1,634	1.833	92	-	215	668

Table 2: Portfolio Risk by Geographic Spread, 1994-2011

Table 2 provides summary statistics about U.S. banks' portfolio risk of their bank branch networks. Portfolio risk is defined as in section 4.1.2. Each section shows the number of banks and the corresponding portfolio risk; the final row "% change" shows the percentage change in the number of banks or in the portfolio risk measure between 1994 and 2011. (†) The column "Std dev" shows the average annual standard deviation.

Year	All Banks		Unit Banks		Non-Unit Banks		Banks with Branches in up to 2 counties		Banks with Branches in 3 to 10 counties		Banks with Branches in >11 counties	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1994	12,954	1.878	4,757	1.782	8,197	1.933	11,319	1.884	1,420	1.848	215	1.744
1995	12,245	1.872	4,320	1.781	7,925	1.922	10,598	1.879	1,423	1.842	224	1.736
1996	11,661	1.869	3,965	1.779	7,696	1.915	9,963	1.877	1,476	1.834	222	1.714
1997	11,150	1.865	3,738	1.79	7,412	1.903	9,435	1.876	1,505	1.818	210	1.711
1998	10,712	1.86	3,492	1.788	7,220	1.896	8,976	1.867	1,523	1.845	213	1.714
1999	10,319	1.858	3,263	1.788	7,056	1.891	8,561	1.862	1,551	1.854	207	1.726
2000	10,093	1.86	3,169	1.79	6,924	1.891	8,302	1.866	1,567	1.845	224	1.716
2001	9,732	1.857	3,000	1.785	6,732	1.889	7,880	1.862	1,628	1.851	224	1.722
2002	9,451	1.857	2,821	1.789	6,630	1.885	7,558	1.862	1,666	1.85	227	1.71
2003	9,241	1.855	2,669	1.786	6,572	1.883	7,295	1.861	1,714	1.848	232	1.715
2004	9,048	1.855	2,559	1.789	6,489	1.881	7,059	1.863	1,769	1.839	220	1.746
2005	8,838	1.851	2,417	1.799	6,421	1.871	6,804	1.859	1,804	1.834	230	1.754
2006	8,749	1.849	2,367	1.8	6,382	1.867	6,611	1.858	1,886	1.829	252	1.756
2007	8,585	1.851	2,280	1.807	6,305	1.867	6,359	1.866	1,968	1.814	258	1.754
2008	8,424	1.849	2,140	1.803	6,284	1.865	6,159	1.866	2,003	1.813	262	1.734
2009	8,168	1.845	2,014	1.787	6,154	1.864	5,901	1.861	1,998	1.813	269	1.722
2010	7,810	1.838	1,858	1.781	5,952	1.855	5,572	1.857	1,971	1.801	267	1.712
2011	7,512	1.833	1,756	1.784	5,756	1.848	5,297	1.854	1,938	1.793	277	1.727
Average	-	1.856	-	1.789	-	1.885	-	1.866	-	1.832	-	1.728
Std dev†	-	0.691	-	0.714	-	0.678	-	0.713	-	0.612	-	0.474
% chg.	-42.00%	-2.40%	-63.10%	0.10%	-29.80%	-4.40%	-53.20%	-1.60%	36.50%	-3.00%	28.80%	-1.00%

Table 3: Bank Stability and Local Economic Conditions

Table 3 shows the correlation between local economic conditions (proxied by local labor market and local real estate declines) and two measures of bank stability. Columns (1) to (4) use a logistic regression as bank failure is a binary outcome; columns (5) to (8) employ a Tobit framework with a lower bound of 0% as capital reserve ratios are non-negative (result unchanged to alternative bounds of 2% or 3%). "Labor market decline" is the maximum percentage increase in the average county unemployment level that a bank faced via its branch network during the crisis period (2008-2011) relative to the baseline in the bank's network in 2006. The variable "real estate market decline" is the largest average county-level real estate decline (proxied by construction costs of new residential buildings) that a bank faced in its branch network during the crisis period (2008-2011) relative to the pre-crisis period (2003-2006). "Bank types" refer to an FDIC-determined institution's primary asset specialization, including a bank being a mortgage-, consumer-, commercial- or "other type" specialist. Balance sheet bank controls are pre-crisis averages from June 2006-June 2007 and are standardized. All variables are winsorized at the 1% level to protect the results from outliers and all regressions employ heteroskedastic error terms with clustering on the state level to allow for differences across states in banking regulation enforcement. Reported coefficients in columns 1-4 are the marginal effects at the mean and median. 2-sided z-statistics (columns 1-4) and t-statistics (columns 5-8) are reported in square brackets.

		Bank Failure (2008-2011)				**Min. Risk-Wght. Capital Reserves (2008-2011)**			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor Market	Mean	0.028 [3.12]	0.032 [3.92]	0.009 [1.76]	0.016 [2.33]	-2.217	-1.856	-1.252	-0.998
Decline	Median	0.028 [3.28]	0.032 [4.07]	0.017 [2.01]	0.027 [3.16]	[-2.87]	[-2.91]	[-2.54]	[-3.15]
Real Estate	Mean	0.097 [2.21]	0.211 [3.17]	0.079 [2.86]	0.155 [3.09]	-0.732	-2.107	-1.075	-0.353
Market Decline	Median	0.097 [2.13]	0.211 [3.05]	0.166 [2.77]	0.257 [3.16]	[-0.50]	[-1.52]	[-1.28]	[-0.33]
Bank Assets				0.004 [0.74]	0.025 [1.67]			2.126 [1.12]	-0.885 [-1.54]
Return on Equity				-0.002 [-0.57]	-0.045 [-2.64]			-1.722 [-2.84]	0.934 [0.67]
Return on Assets				0.005 [0.84]	0.052 [1.33]			1.687 [1.10]	-3.246 [-0.43]
Net Income				0.004 [0.73]	-0.001 [-0.04]			0.614 [-0.32]	-0.418 [-0.64]
Net Operating Income				-0.004 [-1.01]	0.069 [0.80]			7.211 [4.24]	6.961 [0.34]
Asset Growth Rate				0.012 [3.85]	0.015 [2.67]			-2.293 [-5.53]	-1.327 [-2.07]
Equity				-0.094 [-1.01]	-0.025 [-1.88]			-1.521 [-0.54]	1.404 [1.46]
Deposits				-0.003 [-0.61]	-0.001 [-0.09]			-1.293 [-1.19]	0.113 [0.14]
Risk-wght. Capital Reserves				-0.001 [-4.06]	-0.007 [-3.86]			0.865 [8.87]	1.137 [3.31]
Fixed effects for bank types		No	No	Yes	Yes	No	No	Yes	Yes
Condition		$\geq$1 Branch	$\geq$5 Branches	$\geq$1Branch	$\geq$5 Branches	$\geq$1Branch	$\geq$5 Branches	$\geq$1Branch	$\geq$5 Branches
N		8,056	2,770	7,085	2,319	7,278	2,478	7,255	2,470

Table 4: Capital Ratios and Geographic Diversification

Panel A: Univariate Results

	Number of Bank Branches	Number of Counties with Bank Presence: 1 county	2-5 counties	6-10 counties	>10 counties	Freq. adj. avg.
Annual avg. 2002-11	1 Branch	23.7	.	.	.	*23.7*
	2-5 Branches	17.5	15.8	.	.	*16.6*
	6-10 Branches	15.3	14.3	14.0	.	*13.5*
	11-50 Branches	15.1	13.8	13.5	13.9	*13.8*
	>50 Branches	.	13.6	13 .5	12.8	*12.9*
	Freq. adj. average	*20.4*	*15.1*	*13.6*	*13.2*	*17.9*
2006 only	1 Branch	34.8	.	.	.	*34.8*
	2-5 Branches	17.7	15.7	.	.	*16.7*
	6-10 Branches	15.0	14.1	16.9	.	*13.3*
	11-50 Branches	15.8	13.4	12.9	15.4	*13.6*
	>50 Branches	.	12.6	12.3	11.8	*11.9*
	Freq. adj. average	*26.2*	*15.0*	*13.7*	*13.5*	*20.9*

Table 4: Capital Ratios and Geographic Diversification

Panel B: Multivariate Results

Bank controls include measures of bank size (assets, deposits), profitability (return on equity, return on assets, net income, net operating income), investment opportunities (asset growth rate), bank equity and bank types. All Variables are winsorized at the 1% level to protect the results against outliers. Bank types include indicator variables whether a bank is a mortgage-, consumer loan-, commercial loan specialist bank (as determined by the FDIC). Columns 1, 2 and 4 with Newey West standard errors allowing for up 3 orders of autocorrelation, column 3 with first-order autocorrelation robust standard error. 2-sided t-statistics shown in square brackets.

	Dependent Variable: Risk-adjusted Capital Ratio Each coefficient below is obtained from an individual regression in which just one of the measures of geographic diversification was used.			
	(1)	(2)	(3)	(4)
Intercounty Bank	-5.69	-4.48	-0.88	-0.24
	[-46.4]	[-39.2]	[-11.4]	[-0.94]
Interstate Bank	-4.30	-1.80	0.17	-0.24
	[-20.3]	[-8.65]	[1.14]	[-0.94]
Log (branches)	-3.48	-3.37	-0.82	-2.05
	[-49.0]	[-37.6]	[-11.2]	[-10.2]
Log (zip codes)	-3.59	-3.49	-0.81	-2.02
	[-48.9]	[-38.0]	[-11.2]	[-10.2]
Log (counties)	-3.69	-3.22	-0.59	-1.50
	[-45.3]	[-32.4]	[-7.36]	[-8.36]
Avg. Distance	-0.008	-0.004	-0.000	-0.003
	[-4.53]	[-2.70]	[-0.16]	[-1.74]
Max. Dist. > 100m	-4.69	-2.59	-0.35	-0.81
	[-27.1]	[-13.1]	[-2.86]	[-3.28]
Bank Controls	No	Yes	Yes	Yes
Fixed Effects	State,Year	State,Year	State,Year	State,Year
Model	OLS	OLS	Bank-FE	1st Diff.

Table 5: Bank Branching and Bank Stability

Table 5 shows the association between the number of branches and several measures of bank survival for banks with at least 5 branches. Columns (1) and (3) consist of logistic specifications whether a bank failed (i.e., was closed by the FDIC) or survived (i.e., did neither fail nor was acquired) during the crisis period 2008-2011. Reported are marginal effects at the mean (†) and the median (‡) for the variables of interest and at the mean for all other independent variables. Columns (2), (4), and (5)-(8) use OLS regressions to analyze whether the number of branches is correlated to the number of days which a failed bank still survived during the crisis. Columns (6) to (8) use bank Z-Scores that are typically interpreted as the distance towards insolvency. All variables are winsorized at the 1% level to shield results against the effect of outliers; bank balance sheet items are standardized. Bank type controls include indicator variables whether a bank is a mortgage-, consumer loan-, commercial loan specialist bank (as determined by the FDIC). All specifications use heteroskedastic standard errors with clustering on the state level to allow for potential differences in the enforcement of banking regulation across states.

	Measures of Bank Stability (2008-2011)							
Covariates as of 2007	**Bank Failures Failures**	**Failed Banks: Log (days survival)**	**Bank Exists in 2011**	**Non-surviving banks in 2011: Log (days survival)**	**Std Dev. of ROA**	**Average Z-Score 2008-2011**	**Minimum Z-Score 2008-2011**	**Change in Avg. Z-Score pre-to-post**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Branches	-0.020 [-2.33] †	0.114	0.024 [1.30] †	0.092	-0.001	11.192	3.324	-3.037
	-0.034 [-2.47] ‡	[2.33]	0.025 [1.27] ‡	[3.41]	[-1.35]	[1.73]	[1.82]	[-1.72]
Bank Assets	0.017	-0.448	-0.018	-2.43	-0.001	45.724	12.664	7.742
	[1.07]	[-2.08]	[-0.43]	[-0.87]	[-1.61]	[2.95]	[2.21]	[1.26]
Return-on-Equity	-0.043	-0.057	-0.036	-0.028	0.001	-3.76	7.505	-3.083
	[-3.02]	[-0.65]	[-1.07]	[-0.49]	[0.66]	[-0.35]	[1.20]	[-1.45]
Return-on-Assets	0.078	-2.154	0.066	-0.592	-0.003	-45.938	-37.888	-22.43
	[1.73]	[-1.85]	[0.57]	[-1.03]	[-0.65]	[-0.73]	[-1.32]	[-1.34]
Net Income	0.002	-0.06	0.004	0.012	0	-17.444	-5.09	1.124
	[0.16]	[-0.36]	[0.13]	[0.01]	[-0.26]	[-2.03]	[-1.78]	[0.33]
Net Operating Income	0.02	4.559	0.069	8.12	0.005	108.53	63.61	39.073
	[0.21]	[1.97]	[0.25]	[0.77]	[1.35]	[0.87]	[1.27]	[1.33]
Asset Growth Rate	0.02	-0.113	-0.031	-7.33	0.001	-31.407	-10.574	3.859
	[2.22]	[-1.71]	[-2.63]	[-5.69]	[3.49]	[-6.00]	[-5.95]	[2.08]
Equity	-0.021	-0.005	-0.069	0.741	0.002	-15.9	-2.062	-2.13
	[-1.85]	[-0.03]	[-3.18]	[1.03]	[3.32]	[-1.19]	[-0.61]	[-0.68]
Deposits	0.011	0.441	0.058	0.375	0	-26.568	-10.867	-7.087
	[0.65]	[1.33]	[1.43]	[0.33]	[-0.47]	[-2.09]	[-2.54]	[-1.80]
Risk-wght. Capital Reserves	-0.008	0.015	0.009	0.001	0	6.474	2.388	-0.155
	[-3.55]	[1.27]	[1.23]	[0.45]	[-0.18]	[3.52]	[5.02]	[-0.94]
Bank type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,442	145	2,615	452	2,501	2,510	2,510	2,501

Table 6: Bank Stability, Portfolio Diversification & Competition

Table 6 shows the correlation between (1) banks' portfolio risk in 2007 and bank failure, and (2) the degree of competition that banks faced as of 2007 and bank failure during the crisis. Balance sheet items are the average values of the 4 quarterly call reports between June 2006 and June 2007 (i.e., before the crisis). Bank type controls include indicator variables whether a bank is a mortgage-, consumer loan- or commercial loan specialist bank (as determined by the FDIC). Columns 1 and 3 show results for all U.S. banks while columns 2 and 4 show results for banks with at least 5 branches. Reported are the marginal effects at the mean and at the median for the key variables and at the mean for the remainder variables. Columns 5 and 6 use the standard deviation of return on assets as a measure of bank stability during the crisis period. All variables are standardized and winsorized at the 1% level and all specifications include heteroskedastic standard errors that are clustered at the state level to allow for potential differences in the enforcement of banking regulation across states.

		Bank Failed between 2008-2011				**Std. Dev. ROA 2008-2011**	
		(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Risk	Mean	0.011 [1.99]	0.019 [2.69]	0.010 [3.35]	0.016 [3.10]	0.001	0.001
	Median	0.011 [2.04]	0.019 [2.75]	0.017 [3.92]	0.025 [4.28]	[1.61]	[2.47]
Openness to	Mean	-0.006 [-1.26]	-0.018 [-2.54]	-0.002 [-0.79]	-0.009 [-2.24]	-0.001	-0.001
Competition	Median	-0.006 [-1.26]	-0.018 [-2.50]	-0.004 [-0.80]	-0.014 [-2.41]	[-2.64]	[-2.07]
Assets				0.003	0.026		-0.001
				[0.43]	[1.65]		[-1.56]
Return-on-Equity				-0.002	-0.043		0.001
				[-0.55]	[-3.06]		[0.67]
Return-on-Assets				0.005	0.071		-0.003
				[0.90]	[1.46]		[-0.68]
Net Income				0.006	0.001		-0.001
				[0.94]	[0.09]		[-0.27]
Net Operating Income				-0.004	0.023		0.005
				[-1.19]	[0.22]		[1.39]
Asset Growth Rate				0.120	0.018		0.001
				[3.50]	[2.41]		[3.59]
Equity				-0.005	-0.026		0.002
				[-1.20]	[-2.10]		[3.41]
Deposits				-0.002	-0.002		-0.001
				[-0.28]	[-0.14]		[-0.67]
Risk-wght. Capital Reserves				-0.001	-0.008		-0.000
				[-3.57]	[-3.82]		[-0.19]
Bank type Controls		No	No	Yes	Yes	No	Yes
N		8,661	2,921	7,470	2,442	2,512	2,501

Table 7: Bank Stability, Portfolio Diversification & Competition

All variables winsorized at the 1% level and standardized. Bank type controls include indicator variables whether a bank is a mortgage-, consumer loan-, commercial loan specialist bank (as determined by the FDIC). All specifications with heteroskedastic standard errors and clustered at the state level. Columns 8-10 are results from ordinary least squares (logistic specifications provide very similar results). Columns 7 and 10 only on banks with at least 5 branches.

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) Red.Form	(9) Red.Form	(10) Red.Form
Portfolio Risk	0.058	0.079	0.056	0.057	0.058	0.057	0.074	0.038	0.033	0.044
	[4.60]	[2.06]	[4.84]	[4.45]	[4.57]	[4.41]	[4.44]	[4.62]	[4.94]	[4.92]
Openness to Competition	-0.016	-0.020	-0.008	-0.016	-0.016	-0.016	-0.026	-0.015	-0.010	-0.019
	[-2.83]	[-1.88]	[-0.57]	[-2.85]	[-2.92]	[-2.94]	[-3.76]	[-3.16]	[-2.93]	[-4.21]
Bank Assets	0.009	0.011	0.009	0.009	0.009	0.009	0.050	-	0.003	0.041
	[0.86]	[1.03]	[0.82]	[0.85]	[0.86]	[0.85]	[1.52]		[0.26]	[1.18]
Return-on-Equity	-0.003	-0.009	-0.003	-0.003	-0.003	-0.003	-0.028	-	0.002	-0.023
	[-0.29]	[-1.07]	[-0.29]	[-0.28]	[-0.29]	[-0.28]	[-1.86]		[0.16]	[-1.55]
Return-on-Assets	0.017	0.010	0.018	0.017	0.017	0.017	0.096	-	0.007	0.063
	[0.60]	[0.71]	[0.62]	[0.60]	[0.60]	[0.60]	[1.65]		[0.24]	[1.00]
Net Income	0.015	0.013	0.015	0.015	0.015	0.015	-0.000	-	0.009	-0.003
	[1.61]	[1.28]	[1.68]	[1.61]	[1.62]	[1.61]	[-0.00]		[1.01]	[-0.22]
Net Operating Income	-0.030	0.013	-0.031	-0.030	-0.030	-0.030	-0.081	-	-0.017	-0.022
	[-1.19]	[1.57]	[-1.20]	[-1.18]	[-1.19]	[-1.19]	[-0.63]		[-0.70]	[-0.15]
Asset Growth Rate	0.045	0.034	0.045	0.045	0.045	0.045	0.064	-	0.040	0.060
	[3.83]	[3.89]	[3.82]	[3.83]	[3.83]	[3.84]	[4.49]		[3.60]	[4.15]
Equity	-0.015	-0.014	-0.015	-0.015	-0.015	-0.015	-0.028	-	-0.013	-0.027
	[-2.11]	[-1.83]	[-2.14]	[-2.10]	[-2.11]	[-2.10]	[-2.23]		[-1.91]	[-2.20]
Deposits	-0.003	-0.003	-0.004	-0.003	-0.003	-0.004	-0.020	-	0.001	-0.013
	[-0.34]	[-0.35]	[-0.40]	[-0.33]	[-0.35]	[-0.34]	[-0.67]		[0.16]	[-0.42]
Risk-wght. Reserve Capital	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003	-	-0.001	-0.002
	[-2.29]	[-3.27]	[-2.25]	[-2.30]	[-2.29]	[-2.30]	[-3.05]		[-2.54]	[-3.01]
Bank Type Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Instruments used:										
Potential Portfolio Risk	x	-	x	x	x	x	x	x	x	x
Proportion Bankable Area	-	x	-	x	-	x	x	-	-	-
Openness 1997-2005	x	x	-	x	x	x	x	x	x	x
Openness 1978-1997	-	-	x	-	x	x	x	-	-	-
1st Stage F stat. (Portf. Risk)	99.2	5.9	111.1	74.7	83.9	71.3	72.6	n/a	n/a	n/a
1st Stage F stat. (Competition)	110.1	90.6	12.0	69.8	105.5	77.1	102.5	n/a	n/a	n/a
Kleibergen-Paap rk Wald F stat.	102.9	3.64	4.25	80.5	72.2	64.7	75.9	n/a	n/a	n/a
Stock-Yogo Crit. Value (10%)	7.03	7.03	7.03	13.43	13.43	16.87	16.87	n/a	n/a	n/a
Kleibergen-Paap rk LM (p-value)	<0.001	0.079	0.020	<0.001	0.001	0.001	0.001	n/a	n/a	n/a
Hansen's J Statistic	-	-	-	0.293	0.303	1.041	0.681	n/a	n/a	n/a
p-value of Hansen's J	-	-	-	0.589	0.582	0.594	0.712	n/a	n/a	n/a
N	7,370	7,554	7,370	7,367	7,436	7,367	2,553	8,141	7,370	2,554

Table 8A: Bank Stability, Portfolio Diversification & Competition

– Alternative Distress Measures –

All tobit specifications with lower bounds of 0 (results robust to alternative bounds of 2 or 3 percent); all 2SLS specifications with an indicator variable whether the bank failed and an indicator variable if a bank had capital ratios below 3% at any point in time. Bank types indicate whether a bank is a mortgage-, consumer loan-, commercial loan specialist bank (as determined by the FDIC). All specifications with heteroskedastic standard errors and clustered at the state level and all covariates standardized and winsorized at the 1% level. Column 4 for banks with at least 10 branches. Columns 5 and 6 with lower bound of 0 and upper bound of 1,642 days. Column 8 uses a log transformation to reduce the influence of outliers.

	Minimum Capital Reserves (2008-2011)				**Length of Survival for Non-surviving Banks**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobit (no IVs)	Tobit Red. Form IV	2SLS	2SLS (≥ 10 br.)	Tobit (no IVs)	Tobit Red. Form IV	2SLS	2SLS (log)
Portfolio Risk	-0.231	-0.712	-0.684	-0.394	-79.36	-80.54	-151.3	-0.134
	[-1.82]	[-5.77]	[-6.03]	[-2.95]	[-5.22]	[-6.59]	[-6.09]	[-5.60]
Openness to Competition	-0.042	0.096	0.094	0.037	35.02	49.96	60.84	0.060
	[-0.37]	[0.88]	[1.00]	[0.46]	[2.13]	[3.36]	[3.23]	[3.27]
Bank Assets	0.058	0.463	0.312	0.078	-144.9	-193.9	-233.5	-0.239
	[0.14]	[1.10]	[0.74]	[0.29]	[-1.66]	[-2.02]	[-2.54]	[-2.36]
Return-on-Equity	-1.926	-2.357	-2.338	-0.875	30.65	14.40	23.70	0.031
	[-9.10]	[-8.95]	[-8.11]	[-3.80]	[1.26]	[0.57]	[0.80]	[1.08]
Return-on-Assets	2.814	5.673	5.716	-0.200	-62.71	-113.5	-158.2	-0.182
	[5.34]	[4.34]	[4.04]	[-0.20]	[-1.23]	[-1.30]	[-1.62]	[-1.93]
Net Income	0.027	-0.141	-0.094	0.115	-26.16	-25.77	-28.81	-0.026
	[0.12]	[-0.70]	[-0.56]	[0.88]	[-0.96]	[-0.84]	[-0.98]	[-0.85]
Net Operating Income	0.634	-3.341	-3.387	4.445	-68.06	115.2	160.1	0.185
	[1.18]	[-1.62]	[-1.56]	[1.60]	[-1.89]	[1.16]	[1.56]	[1.80]
Asset Growth Rate	-1.510	-1.712	-1.395	-0.346	-134.2	-175.3	-192.8	-0.199
	[-13.15]	[-11.55]	[-10.10]	[-2.90]	[-6.09]	[-7.41]	[-8.42]	[-8.38]
Equity	0.295	-0.014	-0.117	-0.266	87.35	103.1	116.1	0.119
	[1.05]	[-0.05]	[-0.46]	[-0.83]	[2.75]	[3.14]	[3.40]	[3.55]
Deposits	-0.788	-0.596	-0.476	-0.057	84.35	125.3	147.1	0.147
	[-2.88]	[-2.27]	[-1.76]	[-0.21]	[1.48]	[1.94]	[2.42]	[2.11]
Risk-wght. Capital Reserves	0.268	0.295	0.290	0.300	1.307	1.010	0.680	0.001
	[31.0]	[27.7]	[12.0]	[3.77]	[2.77]	[2.49]	[1.44]	[1.71]
Bank Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio Risk 2005	x	-	-	-	x	-	-	-
Openness 2005	x	-	-	-	x	-	-	-
Potential Portf. Risk	-	x	x	x	-	x	x	x
Openness 1997-2005	-	x	x	x	-	x	x	x
1st Stage F stat. (Portf Risk)	n/a	n/a	100.4	98.6	n/a	n/a	55.5	55.5
1st Stage F stat. (Competit.)	n/a	n/a	107.5	186,5	n/a	n/a	156.9	156.9
Kleibergen-Paap rk Walk F stat.	n/a	n/a	101.7	96.45	n/a	n/a	59.8	59.8
Stock-Yogo Crit. Value (10%)	n/a	n/a	7.03	7.03	n/a	n/a	7.03	7.03
Kleibergen-Paap rk LM (p-value)	n/a	n/a	<0.001	0.001	n/a	n/a	<0.001	<0.001
N	7,419	7,136	7,136	1,001	1,163	1,120	1,120	1,120

Table 8B: Bank Stability, Portfolio Diversification & Competition

– Alternative Distress Measures –

All variables winsorized at the 1% level and standardized. Banks with at least 5 branches. Bank type controls include indicator variables whether a bank is a mortgage-, consumer loan-, commercial loan specialist bank (as determined by the FDIC). All specifications with a TARP indicator variable, with bank spread controls (interstate indicator, 100 miles indicator, avg. distance between HQ and branches, no of counties with bank presence, log number of branches) and with heteroskedastic standard errors and clustered at the state level.

	Std Dev of ROA (2008-2011)			**Noncurrent Loans-to-Assets Ratio (2008-2011)**			**Noncurrent Loans-to-Loans Ratio(2008-2011)**		
	(1) No IVs	(2) Reduced form IV	(3) 2SLS (2IVs)	(4) No IVs (tobit)	(5) R.form IV (tobit)	(6) 2SLS (2IVs)	(7) No IVs (tobit)	(8) R.form IV (tobit)	(9) 2SLS (2IVs)
Portfolio Risk	0.001	0.001	0.001	0.376	0.576	0.565	0.372	0.566	0.519
	[2.78]	[5.06]	[4.54]	[5.03]	[5.35]	[5.97]	[4.87]	[5.12]	[5.22]
Openness to Competition	-0.001	-0.001	-0.001	-0.086	-0.133	-0.115	-0.102	-0.147	-0.127
	[-1.87]	[-3.94]	[-3.31]	[-1.12]	[-2.23]	[-2.50]	[-1.44]	[-2.47]	[-2.81]
Bank Assets	-0.002	-0.002	-0.002	-0.444	-0.393	-0.200	-0.380	-0.333	-0.214
	[-1.83]	[-1.75]	[-1.78]	[-2.10]	[-1.89]	[-2.05]	[-1.69]	[-1.56]	[-2.38]
Return-on-Equity	0.001	0.001	0.001	-0.617	-0.530	-0.222	-0.431	-0.351	-0.149
	[0.67]	[0.81]	[0.75]	[-3.28]	[-3.11]	[-2.89]	[-2.19]	[-2.01]	[-1.95]
Return-on-Assets	-0.003	-0.003	-0.002	0.233	-0.019	0.206	-0.712	-0.939	-0.436
	[-0.69]	[-0.78]	[-0.61]	[0.27]	[-0.02]	[0.34]	[-0.84]	[-1.22]	[-0.62]
Net Income	0.000	-0.001	-0.001	0.285	0.274	0.152	0.250	0.228	0.126
	[-0.01]	[-0.27]	[-0.14]	[1.88]	[1.79]	[1.67]	[1.75]	[1.64]	[1.36]
Net Operating Income	0.005	0.005	0.004	1.994	2.305	0.510	3.271	3.599	1.604
	[1.36]	[1.38]	[1.08]	[1.01]	[1.35]	[0.45]	[1.74]	[2.15]	[1.19]
Asset Growth Rate	0.001	0.001	0.001	0.339	0.328	0.255	0.297	0.309	0.227
	[3.43]	[3.68]	[3.86]	[3.70]	[4.38]	[4.39]	[3.23]	[4.48]	[4.26]
Equity	0.002	0.002	0.002	-0.143	-0.197	-0.052	-0.083	-0.158	-0.018
	[3.84]	[3.78]	[3.97]	[-0.86]	[-1.17]	[-0.53]	[-0.47]	[-0.94]	[-0.18]
Deposits	0.000	-0.001	-0.001	0.367	0.305	0.139	0.289	0.266	0.152
	[-0.09]	[-0.14]	[-0.22]	[1.22]	[0.94]	[0.74]	[0.99]	[0.91]	[0.86]
Risk-wght. Capital Reserves	0.000	0.000	0.000	-0.041	-0.035	-0.018	-0.022	-0.012	-0.008
	[-0.43]	[0.03]	[-0.19]	[-3.08]	[-2.33]	[-3.22]	[-1.83]	[-1.17]	[-1.83]
Bank Spread Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TARP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F stat. (Portf. Risk)	n/a	n/a	121.2	n/a	n/a	121.2	n/a	n/a	121.2
1st Stage F stat. (Competit.)	n/a	n/a	157.4	n/a	n/a	156.9	n/a	n/a	156.9
Kleibergen-Paap rk Wald F stat.	n/a	n/a	132.1	n/a	n/a	132.4	n/a	n/a	132.4
Stock-Yogo Crit. Value (10%)	n/a	n/a	7.03	n/a	n/a	7.03	n/a	n/a	7.03
Kleibergen-Paap rk LM (p-value)	n/a	n/a	<0.001	n/a	n/a	<0.001	n/a	n/a	<0.001
N	2,501	2,445	2,445	2,510	2,454	2,454	2,510	2,454	2,454

Table 9: Further Robustness Tests

All variables winsorized at the 1% level and standardized. Bank performance and bank type controls are the same as in Tables 7 and 8. Column (1) with an TARP indicator variable. Column (2) with bank spread controls (interstate indicator, 100 miles indicator, avg. distance between HQ and branches, number of counties with bank presence, log number of branches; robust to using alternative set of spread controls). Columns (3)-(6) address concerns that real estate business cycles may be worse along water bodies. Columns (7) and (8) address concerns that bank headquarter location may be chosen endogenously to have distinct business cycles nearby.

		Bank Failed between 2008-2011							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Portfolio Risk		0.061	0.063	0.045	0.051	0.050	0.042	0.030	0.023
		[4.69]	[4.93]	[2.33]	[2.14]	[2.61]	[3.30]	[3.03]	[2.55]
Openness to Competition		-0.016	-0.015	-0.013	-0.024	-0.013	-0.012	-0.010	-0.007
		[-2.72]	[-2.60]	[-1.34]	[-1.32]	[-2.26]	[-1.31]	[-1.96]	[-1.86]
Geographic Modification	No Salt-Water States	-	-	x	-	-	-	-	-
Geographic Modification	No Sweet- or Salt-Water States	-	-	-	x	-	-	-	-
Geographic Modification	Bankable Area >90% (Spec. 1; land-based)	-	-	-	-	x	-	-	-
Geographic Modification	Bankable Area Q1-Q3 (Spec. 2; slope-based)	-	-	-	-	-	x	-	-
Bank Age	Bank established before 1978	-	-	-	-	-	-	x	-
Bank Age	Bank established before 1934	-	-	-	-	-	-	-	x
TARP Classification		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Spread Controls		No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Type Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Bank Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F stat. (Portf. Risk)		102.8	95.2	81.5	65.5	147.2	228.2	151.2	142.9
1st Stage F stat. (Competit.)		109.6	109.1	159.9	37.3	51.6	121.6	102.9	118.8
Kleibergen-Paap rk Wald F stat.		104.6	96.8	26.8	12	137.6	183.4	99.9	95.5
Stock-Yogo Crit. Value (10%)		7.03	7.03	7.03	7.03	7.03	7.03	7.03	7.03
Kleibergen-Paap rk LM (p-value)		<0.001	<0.001	<0.001	0.002	<0.001	<0.001	<0.001	<0.001
N		7,370	7,370	4,745	4,129	5,232	4,040	5,509	4,071

Table 10: Geographic Diversification and Earnings Volatility, 1994-2011

Columns (1) and (2) show the unconditional correlation coefficient and its significance level between the standard deviation of RoA (based on a rolling 4-quarters window) and the standard deviation of Portfolio Risk and Potential Portfolio Risk (obtained from a 200 miles radius around a bank's headquarter).

Standard Deviation of ROA with Portfolio Risk		
Year	**Portfolio Risk Coefficient** (1)	**Potential Portfolio Risk Coefficient** (2)
1994	0.002 [0.31]	0.040 [2.99]
1995	0.003 [0.40]	0.044 [3.38]
1996	-0.005 [-0.67]	0.069 [4.86]
1997	0.002 [0.29]	0.050 [3.56]
1998	-0.017 [-2.19]	0.006 [0.48]
1999	-0.009 [-1.02]	0.040 [2.87]
2000	0.011 [1.19]	0.079 [5.79]
2001	-0.001 [-0.07]	0.054 [3.93]
2002	0.005 [0.54]	0.060 [4.04]
2003	0.006 [0.55]	0.042 [2.94]
2004	0.015 [1.61]	0.056 [4.03]
2005	0.003 [0.32]	0.048 [3.57]
2006	-0.012 [-1.28]	0.011 [0.91]
2007	0.009 [0.86]	0.045 [3.17]
2008	0.068 [5.34]	0.229 [12.87]
2009	0.130 [8.69]	0.378 [18.99]
2010	0.120 [7.80]	0.332 [16.09]
2011	0.124 [8.47]	0.284 [14.24]

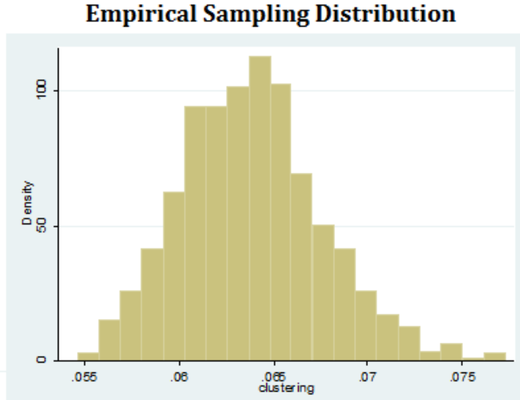
Appendix 1: Geographic Clustering of Bank Failures

The goal is to compute a statistic that represents the degree to which geographic clustering occurs in a network of geographic points (here, the bank network of 453 banks that failed between January 2008 and July 2012). Once such a sample statistic is obtained, its statistical significance is needed.

Step 1: For each of the 453 points in the failed bank network, I count the number of failed banks in the network within a 200 miles radius and divide that number by 452. Thus, for *each* failed bank, I obtain the probability that another *randomly chosen* bank from the failed bank network is within 200 miles.[29] If geographic clustering in the network was high, we would expect to get high probabilities; if however failed banks were thinly spread out across the U.S., we would expect to get low probabilities. I then take the average of the 453 probabilities to arrive at the average probability that a randomly chosen bank in the network is within 200 miles. I find for the failed bank network an average probability of 10.005%. Hence, for the average bank in the failed bank network, there is a 10.005% chance that another randomly chosen failed bank is within 200 miles distance.

Step 2: At this point, it is not yet clear whether a probability of 10.005% indeed indicates clustering relative to the population of all banks. After all, the population of all 8,588 U.S. banks that existed as of Jan 1st, 2007 could be themselves geographically clustered. For that reason, I draw 1,000 random samples of size 453 from the population of all banks and repeat step 1 for each randomly drawn bank network. The procedure provides the empirical sampling distribution of the clustering statistic, which has a mean of 6.384% and a standard deviation of 0.3708% (Figure A.1).

Empirical Sampling Distribution



Sampling distribution of 1,000 average probabilities computed from randomly dran bank networks of size 453 each as described in the text above.

Figure A.1: Empirical Sampling Distribution of Geographic Clustering Statistic

The clustering statistic of the failed bank network (10.005%) lies 9.77 standard deviations to the right of the mean and is located in the top percentile of the empirical sampling distribution. I therefore conclude that the geographic clustering in the failed bank network is significantly higher than the average clustering in the general bank population.

[29]Distances are calculated between bank headquarters' GPS locations as obtained by the FDIC. The results are robust to alternative distances such as 50 or 100 miles.

Appendix 2: State Interstate Branching & Banking Restrictions

State-level interstate branching/banking restrictions pre and post the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (effective 1997).† indicates that reciprocity is required to have more lenient regulations apply. Interstate banking pre-1997 (column 1) indicates the first year in which a state entered an agreement with another state to allowed out-of-state banks to acquire in-state banks (the acquiring bank could however not consolidate banking operations but had to run the target as an independent institution). More information on the data in section 4.1.5 and on the construction of competition-related measures in 5.4. Data sources: Johnson and Rice (2008) and Kroszner and Strahan (1999).

	Pre-1997	**1997-2005**				
State	Interstate Banking Permitted (1)	Date for Effectiveness (2)	*de novo* branching (3)	Minimum Age to be acquirable (4)	Part-acquisition permitted (5)	Deposit cap for acquisitions (6)
AK	1982	1/1/1994	No	3	Yes	50
AL	1987	5/31/1997	No	5	No	30
AR	1989	6/1/1997	No	5	No	25
AZ	1986	8/31/2001	No	5†	Yes†	30
CA	1987	9/28/1995	No	5	No	30
CO	1988	6/1/1997	No	5	No	25
CT	1983	6/27/1995	Yes†	5	Yes†	30
DC	1985	6/13/1996	Yes	0	Yes	30
DE	1988	9/29/1995	No	5	No	30
FL	1985	6/1/1997	No	3	No	30
GA	1985	5/10/2002	No	3	No	30
HI	-	1/1/2001	Yes	0	Yes	30
IA	1991	4/4/1996	No	5	No	15
ID	1985	9/29/1995	No†	5†	No†	100†
IL	1986	8/20/2004	Yes†	5†	Yes†	30†
IN	1986	7/1/1998	Yes	5	Yes	30
KS	1992	9/29/1995	No	5	No	15
KY	1984	3/22/2004	No	0	No	15
LA	1987	6/1/1997	No	5	No	30
MA	1983	8/2/1996	Yes†	3†	Yes†	30
MD	1985	9/29/1995	Yes	0	Yes	30
ME	1978	1/1/1997	Yes†	0	Yes†	30
MI	1986	11/29/1995	Yes†	0	Yes†	100
MN	1986	6/1/1997	No	5	No	30
MO	1986	9/29/1995	No	5	No	13

(Appendix 2 continued)

State	Pre-1997 Interstate Banking Permitted (1)	1997-2005 Date for Effectiveness (2)	de novo branching (3)	Minimum Age to be acquirable (4)	Part-acquisition permitted (5)	Deposit cap for acquisitions (6)
MS	1988	6/1/1997	No	5	No	25
MT	1993	3/13/2001	No	5	No	22
NC	1985	7/1/1995	Yes	0†	Yes†	30
ND	1991	8/1/2003	Yes	0†	Yes†	25
NE	1990	5/31/1997	No	5	No	14
NH	1987	1/1/2002	Yes	0†	Yes†	30
NJ	1986	4/17/1996	No	0	Yes	30
NM	1989	6/1/1996	No	5	No	40
NV	1985	9/29/1995	No	5	No	30
NY	1982	6/1/1997	No	5	Yes	30
OH	1985	5/21/1997	Yes	0	Yes	30
OK	1987	5/17/2000	Yes	0†	Yes†	20
OR	1986	7/1/1997	No	3	No	30
PA	1986	7/6/1995	Yes	0†	Yes†	30
RI	1984	6/20/1995	Yes	0†	Yes†	30
SC	1986	7/1/1996	No	5	No	30
SD	1988	3/9/1996	No	5	No	30
TN	1985	3/17/2003	Yes†	3	Yes†	30
TX	1987	9/1/1999	Yes†	0	Yes†	20
UT	1984	4/30/2001	Yes†	5	Yes	30
VA	1985	9/29/1995	Yes†	0	Yes	30
VT	1988	1/1/2001	Yes†	0	Yes	30
WA	1987	5/9/2005	Yes†	5	Yes†	30
WI	1987	5/1/1996	No	5	No	30
WV	1988	5/31/1997	Yes†	0	Yes†	25
WY	1987	5/31/1997	No	3	No	30

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