Geographic Diversification and Ex Post Commercial Bank Insolvency Risk

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Abstract

There has been a great deal of consolidation in the U.S. commercial banking industry since the banking crisis of the 1980s and early 1990s, leading to greater geographic diversification in the industry. Throughout this consolidation process studies have attempted to measure the effects of greater geographic diversification on insolvency risk. Data on commercial bank failures from the recent financial crisis allow for different techniques in estimating these effects, as well as the ability to compare estimates across the two banking crises. Using a logit model, this paper finds that, ceteris paribus, more geographically diversified banks exhibited a lower probability of insolvency during both banking crises, with the magnitude of these effects being smaller in the recent banking crisis. Furthermore, allowing for portfolio choices to vary, and holding commercial bank size constant, banks with greater geographic diversification during the crisis of the 1980s and 1990s were overall less likely to become insolvent, while there is no systematic difference in the overall probability of insolvency during the recent crisis.

1 Introduction

Geographic diversification in the United States commercial banking industry greatly increased following a period of bank branching deregulation beginning in the 1980s, and ending with passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. While many states allowed for some form of intrastate branching prior to this wave of deregulation, interstate branching was highly restricted by regulations, severely limiting the ability of commercial banks to effectively diversify geographically.[1]. The Riegle-Neal Act permitted full interstate bank branching beginning in 1997, ushering in a long period of commercial bank consolidation in the United States. Due to possible risk-return trade-off choices on the part of commercial banks, it is ambiguous whether greater geographic diversification in the commercial banking industry ultimately leads to greater or less insolvency risk. The answer to this question is of importance to both industry regulators and to the industry itself.

The period between the financial crisis of the 1980s and early 1990s, and the most recent financial crisis, was one of extraordinary stability in the commercial banking industry in terms of bank failures. In the 11 years from June 30, 1997 to June 30, 2008 there were a total of 40 commercial bank failures in the U.S.[2] Over this same period of time, the number of commercial banks headquartered in the U.S. fell from 9,228 to 7,123, evidencing the high degree of consolidation in the U.S. since Riegle-Neal was enacted. Employing a logistic regression, this paper makes use of data on banks that failed during the previous and most recent financial crises in order to estimate the ceteris paribus effect of geographic diversification on the insolvency risk faced by commercial banks during both crises, and to compare these effects across crises. To my knowledge this methodology has not been used for estimating the effects of geographic diversification on insolvency risk during either crisis. In fact, no study has attempted to estimate this effect using any methodology for the post-2007 period. I find that increased geographic diversification significantly decreased the

[1] For a complete history of branching laws in the United States, see Calomiris (2000)

[2] Statistics from the FDIC failed bank list.

probability of failure for commercial banks in both of the crises in question. The reduction in the probability of failure was greater during the previous crisis.

Commercial banks that are able to reduce ceteris paribus insolvency risk through greater geographic diversification may then choose to increase expected revenue streams by engaging in higher return, higher risk investments. This could be done in different ways; banks may decrease their equity-to-asset ratio, increase the amount of high risk loans they make, and invest in riskier non-loan assets such as mutual funds, etc. Therefore, if one finds that, all else equal, greater geographic diversification results in lower insolvency risk, it may still be the case that commercial banks with greater geographic diversification are ultimately more risky due to engaging in riskier behavior along other dimensions. This paper provides evidence that geographically diverse banks did not hold riskier portfolios in the prior crisis, but did in the most recent crisis, namely through lowering their equity-to-asset ratio and becoming more highly leveraged.

2 Economic Theory and Previous Empirical Results

A bank fails,i.e., becomes insolvent if one of two events occurs; either the bank is unable to meet present financial obligations or the Federal Deposit Insurance Corporation (FDIC) puts the bank under receivership and begins the process of winding down the bank, or finding a partner for a forced merger. Since the FDIC Improvement Act of 1991, the FDIC begins the process of winding down a commercial bank when the tangible equity ratio, equal to equity less intangible assets such as goodwill and preferred stock, divided total assets, falls below .02. A bank's equity level provides a buffer between different potential shocks that a bank may be subject to, and insolvency.

Since at any given time commercial banks have incomplete control over equity levels, any particular shock to equity of sufficient magnitude, or a series of shocks to equity of sufficient cumulative magnitude, can lead to insolvency. These shocks can come from three main sources: shocks to asset values, liquidity shocks, and shocks to current revenue or cost streams. Shocks to asset values occur due to decreased market prices and decreased expected revenue streams from said assets. Shocks to liquidity generally occur if demand deposits are unexpectedly withdrawn from branch offices, leaving the bank with less cash and other liquid assets to meet short-term obligations. In order to meet short-term obligations a commercial bank may subsequently be forced to sell traditionally illiquid assets at lower than market values or to acquire liquid assets, such as short-term interbank loans, often at prices significantly higher than demand deposit prices. Shocks to revenue and cost streams occur if assets suddenly stop producing revenue, such as loans becoming past due, or if operating costs increase for unexpected reasons, whether this be the liability access issues presented above or unexpected litigation costs, etc. Note that shocks to revenue streams may lead to subsequent asset value shocks insofar as they translate into lower expected future revenue streams from assets and require the commercial bank to write down the values of these assets.

Markowitz (1952) first investigated the benefits of portfolio diversification and many researchers have since added to the literature on portfolio theory. Geographic diversification, in particular, may decrease insolvency risk by reducing the variance of the underlying distributions for asset value shocks, liquidity shocks, and revenue or cost stream shocks. If local economic conditions play a role in driving the various shocks to which commercial banks are exposed, and local economic conditions are less than perfectly correlated, then geographic diversification may reduce the overall variance of these shocks. Researchers arguing for the deregulation of commercial bank branching in the 1980s made similar arguments (e.g. Department of Treasury (1981), Calomiris et al. (1987), and Wheelock (1992)). Note that, as Levonian (1994) points out, this reduction in overall variance may not be true for any one bank choosing to expand into a new geographic market if the new market has a higher shock variance than markets in which the bank already operates.

Commercial banks that are able to reduce insolvency risk through greater geographic diversification may choose to increase expected revenue streams by engaging in higher return-higher risk investments, within the bounds allowed by regulators. This could be done in different ways; banks may decrease their equity-to-asset ratio, increase the amount of high risk loans they make, and invest in riskier non-loan assets such as mutual funds, etc. In terms of insolvency risk this could be modeled as Figure 1. Curve **I** represents a bank with a ceteris paribus lower geographic diversity level while curve **II** represents a bank with a higher level of geographic diversification. A commercial bank, if operating efficiently, will choose a point on its respective risk-return curve based upon that bank's risk preference.

The following example will help illustrate the concept. A risk-averse bank, or a bank being constrained in its actions by regulation, may choose point **A** on curve **I**. If this bank similarly becomes more geographically diversified, and is now operating on curve **II**, while they will enjoy higher returns, may choose a point in which overall risk is decreased, such as (**B**), or a point in which overall risk is increased, such as (**C**). This choice will be determined by that banks risk preference expansion. Whether a bank chooses to increase or decrease ex ante insolvency risk is dependent on the risk preference for that bank. The question of overall changes in insolvency risk due to increased geographic diversification is thus empirical in nature.

The financial crisis of the 1980s and early 1990s led to a series of empirical studies seeking to determine the affect of geographic diversification on the insolvency risk of bank holding companies (BHCs) over the time period of the crisis. A consensus exists in terms of the affect that geographic diversification has on insolvency risk, holding certain portfolio composition measures constant. Of the five studies estimating this ceteris paribus effect, three find unambiguous and significant decreases in insolvency risk due to geographic diversification (Liang and Rhoades (1988), Rivard and Thomas (1997), and Demsetz and Strahan (1997)). Of the two remaining studies, Rose (1996) finds a decrease in insolvency risk for already diverse banks, while Emmons et al. (2004) finds a decrease in insolvency risk for urban commercial banks with assets in a single county. These studies use differing methodologies, measures of risk, unit of observation, and time frame. These differences and the results for all empirical studies cited in this paper are presented as Table 1 for the readers convenience.

A similar consensus is not present in the studies that estimate whether more geographically diverse BHCs have higher overall insolvency risk. Liang and Rhoades (1988) find a decrease in overall insolvency risk for more geographically diverse banks. On the other hand, Chong (1991) and Hughes et al. (1996) find an increase in overall insolvency risk. Lastly, Akhigbe and Whyte (2003) find no significant effect for banks with assets in one state, and a significant decrease in insolvency risk for banks with assets in multiple states. It is difficult to pinpoint the cause of this disagreement, as the methodologies and time frames used by the studies differ. Again, these studies are roughly characterized in Table 1.

Technologies developed within the commercial banking industry give reason to believe the importance that geographic diversification has on commercial bank insolvency risk may have changed since the financial crisis of the 1980s. While Berger and DeYoung (2006) show that technological progress has decreased the costs of geographic expansion as well as increase the ability of commercial banks to exert central control over, and export efficiencies to, bank branches, recent technological progress may have also decreased the need for geographic diversification. Increased securitization of loans as well as online loan origination may have decreased the importance of physical branch diversification for the purpose of diversifying geographic risk associated with asset values. Furthermore, the ability to manage deposit accounts online may have decreased the importance of physical branch diversification for the purpose of diversifying risk associated with demand deposit accounts. On March 30, 2003, approximately 46 percent of commercial banks in the U.S. had a website that allowed for the electronic managing of deposit accounts while on June 30, 2008, that same statistic is approximately 84 percent.[3] In particular, geographic diversification may have become less important as a determinant of insolvency risk during the recent banking crisis as opposed to the prior crisis.

Using data on BHCs from the time period between the previous and most recent crisis,

[3]Statistics from the FDIC quarterly call reports, item rcfd4088.

Deng and Elyasiani (2008) and Goetz et al. (2014) find that, holding portfolio characteristics constant, the significant and negative effect of geographic diversification on insolvency risk persists beyond the previous financial crisis. Furthermore, while neither of the two studies mentioned above include data post-2007, Aubuchon and Wheelock (2010) find evidence that state market conditions are correlated with commercial bank failure in the most recent crisis, leading to an unbalanced level of failures across the United States. The above evidence suggests that geographic diversification is still an important factor determining risk of insolvency.

Three studies estimate whether more geographically diverse banks exhibit higher overall insolvency risk using data from the time period between the two crises. Deng et al. (2007) and Goetz et al. (2014) find that geographically more diverse BHCs exhibit less overall insolvency risk in the time period after the previous crisis. Dick (2006) finds that commercial banks, after the enactment of Riegle-Neal in 1994, choose to engage in greater portfolio risk. These studies suggest that consolidation during the time period between the previous and most recent crisis results in banks with less insolvency risk, even though banks choose riskier portfolios after consolidation.

The majority of empirical literature presented above focuses on estimating the effect of geographic diversification on insolvency risk using either market assessed risk measures, or alternatively, measures based on the volatility of earnings. These studies identify ex ante risk levels conditional on geographic diversity levels. This study proposes to investigate the contribution of geographic diversification, or lack thereof, in determining which banks failed during the two most recent financial crises. In doing so, it is possible to compare these effects across both crises. Carlson (2004) is the only study, of which I am aware, to use data on actual bank failures in estimating the contribution of geographic diversification to bank insolvency, and Carlson is focused on bank failures during the Great Depression. This study adds to the literature on the effects of geographic diversification on the probability of bank failures across the two banking crises of the past half-century.

3 Empirical Methodology and Data

3.1 Methodology

For the main results of this paper a bank will be assumed to fail if capital adequacy (*capad*), dips below a minimum level $capad^{min}$, where *capad* is defined as the ratio of equity minus goodwill to assets[4], or the FDIC puts the bank under receivership. The value $capad^{min}$ is chosen to be 0.02 due to the previously mentioned FDIC Improvement Act of 1991. Define the binary variable $failure_{i,t}$ as

$$failure_{i,t} = \begin{cases} 1 & if \;\; capad_{i,t} \leq 0.02 \\ 0 & if \;\; capad_{i,t} > 0.02 \end{cases}, \tag{1}$$

where i indexes bank, and t denotes year t. Given the definition of $failure$, we can model the probability of commercial bank failure using the logit distribution. Then the probability of failure can be parameterized as

$$P(failure_{i,t} = 1 | \boldsymbol{X_{i,t}}, \boldsymbol{Z_{i,t}}) = \frac{e^{\boldsymbol{\beta X_{i,t}} + \boldsymbol{\alpha Z_{i,t}}}}{[1 + e^{\boldsymbol{\beta X_{i,t}} + \boldsymbol{\alpha Z_{i,t}}}]}, \tag{2}$$

where $\mathbf{X}_{i,t}$ is a vector of covariates representing a commercial bank's equity level, balance sheet composition, liquidity level, current earnings, and geographic diversity, while $\mathbf{Z}_{i,t}$ is a vector of controls. Due to the nature of the available data, *capad* cannot be observed continuously over time. What is observed is whether a bank fell below a *capad* level of 0.02 during a particular time period, leading to the above specification being considered as an application of a latent variable model. This methodology for identifying probability of failure does not identify historic or future *ex ante* risk levels for different asset classes and portfolio positions, but it does allow for identification of shocks, and thus to commercial bank characteristics that led to failure in the prior and most recent financial crises.

[4]This definition of capital adequacy is taken from Wheelock and Wilson (2000)Wheelock and Wilson (2000)

While this study does not attempt to formally model commercial banks' decisions regarding the mix of reduced risk due to geographic diversity and increased revenue, it is possible to present evidence on whether geographically more diverse banks were *overall* more susceptible to shocks than geographically less diverse banks. After controlling for the ceteris paribus effect of geographic diversity it is possible to estimate fitted failure probabilities for different diversity levels. While this would not be proof of causality if geographically more diverse commercial banks are overall more or less risky, it would provide evidence of a link between diversity and decisions to engage in some form of riskier behavior, whatever the mechanism.

3.2 Data

As noted above, commercial bank failure for the main regressions presented in this paper is technically defined as any commercial bank that was officially wound down by the FDIC, including banks that were subsequently acquired by another bank in part or as a whole, as well as any bank whose reported capital adequacy ratio dropped to less than 0.02 during the relevant time period. For example, a commercial bank reporting an equity-to-asset ratio at or below 0.02 on the June 30, 1986 call report would be categorized as failing sometime between April 1, 1986 and June 30, 1986. Data on commercial banks being wound down under FDIC receivership are obtained from the FDIC. Levels of equity-to-assets ratios are explained later in the paper.

For the time period 1985–1992 Delaware and Hawaii suffered no commercial bank failures while many states only experienced 1–3 commercial bank failures. Texas was an epicenter for commercial bank failures as there were 610 failures in that state alone, while neighboring states all had disproportionate numbers of bank failures. A heat map displaying this concentration in the number of failures by state is presented as Map 2a of Figure 2. In all, there were 1501 commercial bank failures representing approximately $350 billion constant 2009 dollars in assets during the period 1985–1992. For the time period 2008–2013 the states with the largest numbers of failures are more spread out geographically, providing some evidence for the idea that the economic shocks leading to the financial crisis were more nationwide phenomena, even if commercial banks failed in localities suffering some form of local shock. A heat map of commercial bank failures by state is presented as Map 2b of Figure 2. There are three main regions for commercial bank failures in the most recent crisis: the Southeast region centered around Georgia and Florida, the Midwest region centered around Illinois, and the West region centered around California. Many states had no commercial bank failures during the most recent crisis. In all there were 417 commercial bank failures representing approximately $382 billion constant 2009 dollars in assets during the period 2008–2013.

The geographic diversity measure used in this study is constructed from the FDIC's Summary of Deposits data. These data include all FDIC insured commercial banks in the United States and reflect deposits as of June 30th for each year, for each bank. The measure of diversity is defined as

$$diverse_i = 1 - \sum_{c=1}^{C} \left(\frac{deposits_{c,i}}{totaldeposits_i}\right)^2, \tag{3}$$

where i denotes bank and c denotes a particular county, which serves as the market in this risk measure. A commercial bank will have a value of zero for *diverse* if all of the bank's deposits are concentrated in a single county. This measure has been used in previous studies such as Hughes et al. (1999), Deng et al. (2007), and Goetz (2012).

Summary statistics for the diversity measures for periods 1985–1992 and 2008–2013 are presented in the first row of Table 2. Commercial banks are more geographically diverse on average for the 2008–2012 sample as opposed to the 1985–1992 sample. Many commercial banks in both sample time periods only take deposits in one county. In fact, 91 percent of banks have a *diverse* value of zero on June 30, 1985, while 50 percent of banks have a *diverse* value of zero on June 30, 2008. While diversity has greatly increased in the interim between the prior and most recent financial crises, there are still a large number of commercial banks operating in only one county.

3.2.1 Asset Exposure Measures

Data for commercial bank asset and equity levels are collected from the FDIC's Quarterly Call Reports of Condition and Income. These call reports are mandatory documentation required of all commercial banks operating within the United States. Data are collected from the June call reports for the years 1985–1992 and 2008–2013 for all commercial banks in the United States, regardless of size. Commercial banks headquartered outside of the U.S. are excluded from the data set. Assets from the balance sheet have been separated into four main categories; cash and balances due from depository institutions(*cash*), securities(*sec*), loans, and other assets. Loans and other assets are further broken down into more granular categories. Other assets are broken out into other real estate owned by the commercial bank(*otherreal*) and all other various assets(*otherasset*), while the breakouts of loans is described in detail below. All asset category levels are transformed into ratios by dividing through total assets of the commercial bank, thus giving them an interpretation of exposure levels to particular asset categories.

Loans are further broken down into the measures presented below. The variable *farm* measures loans secured by farmland as well as loans made to farmers, whether these loans are made to finance agricultural production or otherwise. The variable *resreal* measures loans secured by 1–4 family residential properties. The variable *comhouse* measures loans secured by residential properties meant for 5 or more families. Ideally *resreal* would only include loans secured by single family residential properties while *comhouse* would include loans secured by any multifamily residential properties, but these data are unavailable in the call reports. The variable *dev* measures loans secured by construction, land development, and other land loans. The variable *comreal* measures loans secured by nonfarm, nonresidential properties. The variable *comloan* measures commercial and industrial loans. The variable *otherloan* measures all other loans held by the commercial bank including loans to depository institutions, loans for expenditure purposes, and loans made to governments both foreign and domestic. Again, these loan category levels are transformed into ratios by dividing through total assets of the commercial bank, thus giving them an interpretation of exposure levels to particular loan categories.

3.2.2 Current Earnings and Liquidity Measures

The variable *earn* measures the ratio of income after taxes to assets of the commercial bank. Data on income are collected from the quarterly call reports. Income is a flow variable, and as such, data on income are collected for each year interval starting on July 1st and ending June 30th of the following year. If a commercial bank fails during the interval, then *earn* measures earnings up to the most recent available information.

The variable *liq* measures the liquidity of the commercial bank. The vast majority of short-term obligations on the part of the bank are in the form of demand deposits. A commercial bank may also have short term liabilities or assets in the form of activity in the federal funds market. Thus, the variable *liq* is equal to the ratio of cash plus net federal funds sold to demand deposits.

Control variables include *hold*, *age* and *size*. The variable *hold* is a dummy variable equal to one if the commercial bank is a part of a multi-bank holding company and equal to zero otherwise, *age* is equal to the number of years that the commercial bank has been chartered, and *size* is equal to the log of total assets of the commercial bank in real terms.

3.2.3 Summary Statistics, Non-Diversity Independent Variables

Summary statistics for the above variables are presented as Table 2. There are a number of striking differences between the two samples. *capad* levels are close to two percentage points higher on average in the latter sample, leading to the potential conclusion that as a whole, commercial banks were less risky, as measured by leverage, in the latter period. Note however, that many of the traditionally more risky loan categories take up a larger share of total assets in the latter period. These riskier categories include *comhouse*, *comreal* and *dev*. Increases in the riskier asset classes during the financial crisis come mostly at the expense of *sec*, *otherloan*, and *otherasset*. So while commercial banks in the financial crisis have higher *capad* levels on average, they are also more exposed to classically risky asset classes as well. In fact, loans make up about 62 percent of total commercial bank assets on average in the time period 2008–2013, while the same statistic is about 52 percent in the period 1985–1992.

4 Results

Pooled logit regressions are separately run for the first banking crisis and most recent crisis, corresponding to the time periods of 1985–1992 and 2008–2013 respectively. Due to the fact that, by definition, the asset exposure variables sum to one it is necessary to exclude a category for identification purposes. The asset exposure variable excluded in this study is *cash*. The choice of *cash* was made for ease of inference as *cash* is theoretically a relatively safe asset exposure category. Effects of increasing asset exposure levels for a particular asset classification are thus interpreted as relative to *cash*. Furthermore, the ceteris paribus marginal effects for variables constructed with bank assets as the denominator are due to changes in the numerator, holding the denominator, or total bank assets, constant. Finally, these variables are scaled such that marginal effects reported measure a percentage point change in probability of insolvency for a one percentage point increase in the variable. Variables that are constructed with total bank assets as the denominator include *capad* and all of the asset exposure variables. Year fixed effects are included in both regressions. Coefficients from the logit regression are reported as well as average marginal effects (AMEs) and 95% confidence levels for the AMEs. These regression results are reported in Table 3.

4.1 Results for *capad* and *earn*

The effects of *capad* and *earn* on the probability of insolvency have been found to be negative and significant in all previous studies. This should be no surprise as *capad* is the buffer between losses and insolvency for the commercial bank while *earn* directly decreases equity if a commercial bank suffers losses in a quarter. As other studies have found, increases in *capad* and *earn* are found to decrease the probability of insolvency during both crises. While the AMEs of both of these variables are smaller in magnitude during the most recent crisis, the AMEs are still large in absolute terms. On average, during the first banking crisis, an increase in *capad* of 0.01 resulted in a decrease to the probability of insolvency of 0.60 percentage points. The same effect for the most recent crisis is a decrease in probability of 0.55 percentage points. An increase in income of 1 percent of total assets led to a decrease in the probability of insolvency of 0.37 percentage points during the first crisis and a decrease in the probability of insolvency of 0.23 percent during the most recent crisis.

4.2 Results for Asset Exposure Levels

There are marked differences between the two crises with respect to the effects that different asset exposure levels have on the probability of insolvency. In the first crisis, all asset exposure classifications have significantly different AMEs from *cash* at the 5 percent confidence level. The only classification that has a negative AME on the probability of insolvency during either crisis is *sec* in the first crisis. All other asset classifications have a positive AME on the probability of insolvency during the first crisis, with *otherreal* having the largest effect. A 0.01 unit increase in *otherreal* increased the probability of insolvency by 0.20 percentage points. While there are differences in the AMEs of exposure to various loan categories in the first crisis, most notably that *resreal* has a magnitude of effect multiples smaller than other categories, it is the case that holding loans of any category as opposed to *cash* led to higher levels of insolvency risk. During the most recent crisis this was not the case, as the only loan categories significantly different from *cash* are *comhouse* and *dev*. In the most recent crisis, and similar to the first crisis, *otherreal* has the largest positive AME of all asset classifications on probability of insolvency, with a 0.01 unit increase in *otherreal* increasing the probability of insolvency by 0.11 percentage points on average.

4.3 Results for *size* and *hold*

As many other studies have previously found, an increase in bank size measured by total bank assets is related to a lower probability of insolvency during the first crisis, after controlling for the makeup of a commercial bank's asset portfolio. In the most recent crisis, however, bank size is unrelated to insolvency probability after controlling for a commercial bank's asset portfolio. There will be more on this result later in the paper. The creation of multi-bank BHCs is understood to have been an effective way for commercial banks to access diverse markets before branching deregulation, and, in line with this reasoning, the effect of belonging to one of these BHCs decreased the probability of insolvency during the first crisis. Surprisingly, the negative effect of belonging to a multi-bank BHC on the probability of insolvency persists, albeit of less magnitude, during the most recent crisis, even though most barriers to expansion have been removed.

4.4 Results for *diverse*

The variable *diverse* measuring geographic diversification has the correct sign and is significant at the 5 percent confidence level for both crises. It can be difficult to interpret unit changes in a variable such as *diverse*, and so it may be beneficial to think of a standard deviation change in *diverse*. For example, during the first crisis the **approximate** average decrease in the probability of insolvency from a one standard deviation increase in *diverse* is equal to -0.20 percentage points, while the same effect is equal to -0.11 in the most recent crisis. At first glance these effects may seem economically small.

Simply finding the overall mean of the marginal effects hides interesting information about how these marginal effects differ across banks. A graph of the means of the marginal effect of geographic diversification for different groupings of *diverse* levels for both time periods is presented as Graph 3b of Figure 3. Note that there are systematic differences in the AMEs for different levels of *diverse* during the first crisis. The AMEs are most negative at lower levels of the variable *diverse*, suggesting that there were "low hanging fruit" in terms of future geographic diversification for commercial banks with already low geographic diversity. There seems to be no systematic pattern for the marginal effects on *diverse* during the most recent crisis.

The difference in systematic patterns of marginal effects between the prior and most recent crisis may be due to the fact that during the prior crisis commercial banks were constrained in their branching activities by regulatory legislation. These constraints left many commercial banks unable to capitalize on opportunities to lower insolvency risk through geographic diversification. Graphs 3a and 3c of Figure 3 display histograms of *diverse* levels across banks for the 1985–1992 and 2008–2013 time periods, respectively. Commercial banks with a *diverse* level lower than 0.1 make up a much smaller proportion of banks for the time period 2008–2013. The reduction in the proportion of banks with *diverse* levels less than 0.1 has been approximately distributed evenly across the rest of the distribution of commercial banks. Taken together, this is evidence that banks with the most extreme marginal effects for reducing insolvency risk through geographic diversification have indeed become more diversified.

4.5 Overall Failure Probabilities for Commercial Banks by Diversity Levels

As stated earlier, high levels of geographic diversity measures may be correlated with certain asset class exposure and capital levels. Insofar as there are positive correlations between geographic diversity and the variables that the logit model deemed risky during either crisis, then a commercial bank that is more geographically diverse may in fact have been exposed to more/stronger shocks during either crisis. So, even though, ceteris paribus, higher levels of geographic diversification led to lower insolvency risk in both crises, it may be the case that more geographically diversified banks are overall more likely to fail in either crisis.

Correlations between the diversity measure and asset classification measures as well as *capad* are presented as columns 2 and 5 of Table 4. Note that the correlations generally lead to the conclusion that a more geographically diverse bank is also more likely to be exposed to asset classifications that are *ex post* more risky in both crises.

Since the size of a commercial bank and its geographic diversification are highly correlated, it may be important to control for the tendency that large banks have a risky portfolio when investigating if geographically diverse banks tend towards a relatively risky portfolio. In order to separate these correlations I run a series of OLS regressions of the form

$$y^*_{i,t} = \beta_0 + \beta_1 * diverse_{i,t} + \beta_2 * size_{i,t} + \epsilon_{i,t}, \tag{4}$$

where y^* corresponds to each of the asset exposure classifications and *capad*. Results of these regressions are reported as columns 3–4 and 6–7 of Table 4. Many of the coefficients on *diverse* from these regressions reverse the sign compared to the correlation estimates. After controlling for size, higher geographic diversity is correlated with greater exposure to *farm* and *resreal* in both samples. After controlling for size, higher geographic diversity is correlated with less exposure to *comhouse*, *comreal*, *comloan* and *foreign* in both samples. In other words, banks that have a physical presence in many local markets hold more "localized" loans on their balance sheet on average. Larger banks hold more business and commercial type loans on their balance sheets. The most important difference between the two crises is the estimate for β_1 in the OLS regression on *capad*. In the first period higher levels of *diverse* are unrelated to *capad* levels, while in the most recent crisis higher levels of *diverse* are related to lower levels of *capad*.

As the above analysis shows, it is important to hold size constant in attempting to ascertain if more geographically diverse commercial banks held riskier portfolios in either of the financial crises. As such, fitted values for the probability of insolvency are calculated for each bank, in each time period, holding *size* constant at the mean *size* of the relevant period. Fitted values are constructed using the results of the logit model estimated earlier in the study. These fitted values are then averaged over different levels of *diverse* and presented in Table 5. For the first crisis there is a clear drop in the fitted probability of failure between commercial banks which had all of their deposits in one branch and those banks which had even a slight increase in the geographic dispersion of their deposits across markets. There is no systematic difference in the probability of insolvency across *diverse* levels after the initial decrease in risk of insolvency. There seems to be no pattern in the fitted probabilities of insolvency risk for the most recent crisis.

Taken together, these results suggest a few things. Commercial banks operating one branch in the first crisis were not more capitalized than their highly diversified counterparts, leaving them more vulnerable to exogenous shocks. This could be due to the fact that regulations prevented certain bank managers from reducing risk through geographic diversification, thus leading them to choose a more risky position on the risk-return frontier than they otherwise would. After branch banking deregulation, and the period of consolidation that ensued, a pattern emerges in which more geographically diversified banks are more highly leveraged, thus in some sense spending their risk reduction gains on higher returns. While there are still banks that chose to operate in a single market during the most recent crisis, these banks are highly capitalized banks making more localized loans, such as farming and residential real estate loans.

5 Conclusions

Commercial banks in the United States with higher levels of geographic diversification had lower ex post probabilities of insolvency, all else equal, during both the financial crisis of the 1980s and early 1990s and the most recent financial crisis. The marginal effects on insolvency probability are larger for the first crisis as opposed to the most recent crisis, possibly due to legislatively constrained banks operating in one or a few markets. These large marginal effects present in the earlier crisis disappeared over the course of the 1990s and 2000s, possibly due to changes in technology and possibly due to further geographic diversification. The overall probability of insolvency was lower for more geographically diverse commercial banks during the first crisis, with most of this difference coming from commercial banks that operated in one market. During the most recent crisis there is no clear difference in the overall probability of insolvency across banks with differing levels of geographic diversity. This suggests that, after shifting the risk-reward frontier outwards with geographic expansion, commercial banks chose a similarly risky position on this frontier as before the expansion.

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Table 1: Literature Review Summary

					Result	
	Unit of Obs.	Risk Measure	Time Frame	Methodology	Ceteris Paribus	Overall
Liang and Rhoades (1988)	High Holder	Earnings and Equity	1976-1985	OLS	-	-
Chong (1991)	BHC	Market Assessed	1982-1985	Event Study	na	+
Rose (1996)	BHC	Earnings	1980-1992	OLS	- (geo. diverse banks)	na
					+ (geo. non-diverse banks)	na
Hughes et al. (1996)	BHC	Deposit Volatility, Market Assessed	1994	AIDS (structural)	na	+
Rivard and Thomas (1997)	BHC	Earnings	1988-1991	Recursive Model (OLS)	-	na
Demsetz and Strahan (1997)	BHC	Market Assessed	1980-1993	Factor Analysis	-	na
Akhigbe and Whyte (2003)	High Holder	Market Assessed	1993-1994	Event Study	na	= (assets in one state)
					na	- (assets in multiple states)
Carlson (2004)	State banks (CA, MD, NC)	Failure	1929-1933	Logit	+	na
Emmons et al. (2004)	Banks, assets in single county	SEER, Earnings	1989-1993	SEER Model, OLS	=	na
Dick (2006)	Commercial banks	Loan losses	1993-1999	Event Study	na	+ (portfolio risk)
Deng et al. (2007)	BHC	Bond yield-spreads	1994-1998	OLS	na	-
Deng and Elyasiani (2008)	BHC	Market Assessed	1994-2005	OLS	-	na
Goetz et al. (2014)	BHC	Market Assessed, Earnings	1986-2007	Gravity Model, IV	-	-

Table 2: Summary Statistics

	1985-1992		2008-2013	
Variable	Mean	S.d.	Mean	S.d.
diverse	0.055	0.157	0.229	0.273
capad	0.091	0.043	0.109	0.058
secexp	0.293	0.159	0.214	0.153
farmexp	0.078	0.105	0.088	0.123
resrealexp	0.124	0.091	0.159	0.105
comhouseexp	0.005	0.012	0.015	0.027
comrealexp	0.060	0.058	0.165	0.116
devexp	0.019	0.036	0.055	0.066
comloan	0.112	0.089	0.091	0.068
otherloanexp	0.126	0.092	0.050	0.060
otherrealexp	0.006	0.011	0.007	0.014
otherassetexp	0.096	0.078	0.077	0.062
foreignexp	0.001	0.012	0.000	0.006
liq	0.126	10.922	-3.690	301.490
earn	0.007	0.016	0.004	0.018
hold	0.247	0.431	0.142	0.349
age	58.2	36.6	68.2	44.0
size	11.25	1.23	11.98	1.31

Table 3: Main Logit Regression Results

	1985 - 1992			2008 - 2013		
Variable	Coefficient	Marginal Effect	95% C.I.	Coefficient	Marginal Effect	95% C.I.
capad	-58.523***	-0.601***	-0.643, -0.558	-71.831***	-0.545***	-0.603, -0.487
secexp	-1.473**	-0.015***	-0.027, -0.003	-0.471	-0.004	-0.022, 0.014
farmexp	5.361***	0.055***	0.042, 0.068	0.005	0.015	-0.008, 0.037
resrealexp	1.422**	0.015**	0.001, 0.028	-0.647	-0.005	-0.024, 0.014
comhouseexp	5.429***	0.056**	0.014, 0.098	8.359***	0.063***	0.037, 0.090
comrealexp	6.379***	0.065***	0.051, 0.080	1.114	0.008	-0.010, 0.027
devexp	5.330***	0.055***	0.037, 0.072	9.204***	0.070***	0.051, 0.089
comloan	6.886***	0.071***	0.058, 0.084	-0.479	-0.004	-0.026, 0.019
otherloanexp	5.278***	0.054***	0.042, 0.067	-0.811	-0.006	-0.041, 0.029
otherrealexp	19.579***	0.201***	0.172, 0.229	13.993***	0.106***	0.068, 0.144
otherassetexp	3.731***	0.038***	0.026, 0.051	3.399**	0.026***	0.005, 0.047
foreignexp	5.245**	0.054**	0.003, 0.105	0.202	0.002	-0.143, 0.146
divers	-1.283***	-0.013***	-0.019, -0.008	-0.588**	-0.004**	-0.009, $-3.04e^{-4}$
liq	0.001	$1.40e^{-5}$	$-3.09e^{-4}$, $3.37e^{-4}$	$4.72e^{-5}$	$3.58e^{-7}$	$-8.02e^{-6}$, $8.73e^{-6}$
earn	-36.160***	-0.371***	-4.01, -3.41	-30.726***	-0.233***	-0.270, -0.196
hold	-0.557***	-0.525***	-0.663, -0.387	-0.621***	-0.417***	-0.668, -0.166
age	$3.06e^{-6}$	$3.14e^{-6}$	$1.86e^{-5}$, $2.48e^{-5}$	$-4.50e^{-5}$	$-3.42e^{-5}$	$-2.82e^{-3}$, $2.75e^{-3}$
size	-0.205***	-0.211***	-0.282, -0.139	0.037	0.028	-0.071, 0.127
# of failures		1501			417	
obs		101495			32478	

[a] Marginal effects are average marginal effects.

[b] Confidence intervals are with respect to average marginal effects.

[c] * denotes significance at the 10% level, ** , denotes significance at the 5% level, and ***denotes significance at the 1% level.

Table 4: Correlations and OLS Regression Results, Diversity Measure and Explanatory Variables

	1985 - 1992			2008 - 2013		
	Correlation	OLS Regression		Correlation	OLS Regression	
y^*	*diverse*	β_1	β_2	*diverse*	β_1	β_2
capad	-0.124***	0.001	-0.010***	-0.184***	-0.018***	-0.008***
secexp	-0.104***	-0.048***	-0.016***	-0.102***	-0.042***	-0.006***
farmexp	-0.093***	0.059***	-0.035***	-0.032***	0.091***	-0.041***
resrealexp	0.071***	0.021***	0.006***	0.043***	0.006***	0.004***
comhouseexp	0.039***	-0.002***	0.001***	0.049***	-0.007***	0.005***
comrealexp	0.106***	-0.005***	0.013***	0.142***	-0.008***	0.027***
devexp	0.087***	-0.001	0.006***	0.125***	-0.002	0.013***
comloan	0.071***	-0.019***	0.017***	0.034***	-0.009***	0.007***
otherloanexp	0.103***	0.006***	0.015***	-0.032***	-0.015***	0.003***
otherrealexp	-0.035***	-0.001***	-3e^{-4}***	0.048***	0.002***	1e^{-4}***
otherassetexp	-0.052***	-0.012***	-0.004***	-0.015***	-9e^{-5}	-0.001***
foreignexp	0.085***	-0.001***	0.002***	0.018***	-0.002***	0.001***
size	0.442***	——	——	0.532***	——	——
obs	101080			32221		

[a] * denotes significance at the 10% level, ** , denotes significance at the 5% level, and ***denotes significance at the 1% level.

Table 5: Fitted Probabilities

	Mean Fitted Probability	
diverse level	1985-1992	2008-2013
$0.0 \geq diverse < 0.1$	0.157	0.0117
$0.1 \geq diverse < 0.2$	0.0112	0.0159
$0.2 \geq diverse < 0.3$	0.0092	0.0145
$0.3 \geq diverse < 0.4$	0.0081	0.0154
$0.4 \geq diverse < 0.5$	0.0088	0.0124
$0.5 \geq diverse < 0.6$	0.0104	0.0148
$0.6 \geq diverse < 0.7$	0.0101	0.0103
$0.7 \geq diverse < 0.8$	0.0108	0.0161
$0.8 \geq diverse < 0.9$	0.0122	0.0097
$0.9 \geq diverse \leq 1.0$	0.0071	0.0150

Figure 1: Risk-Reward Frontier

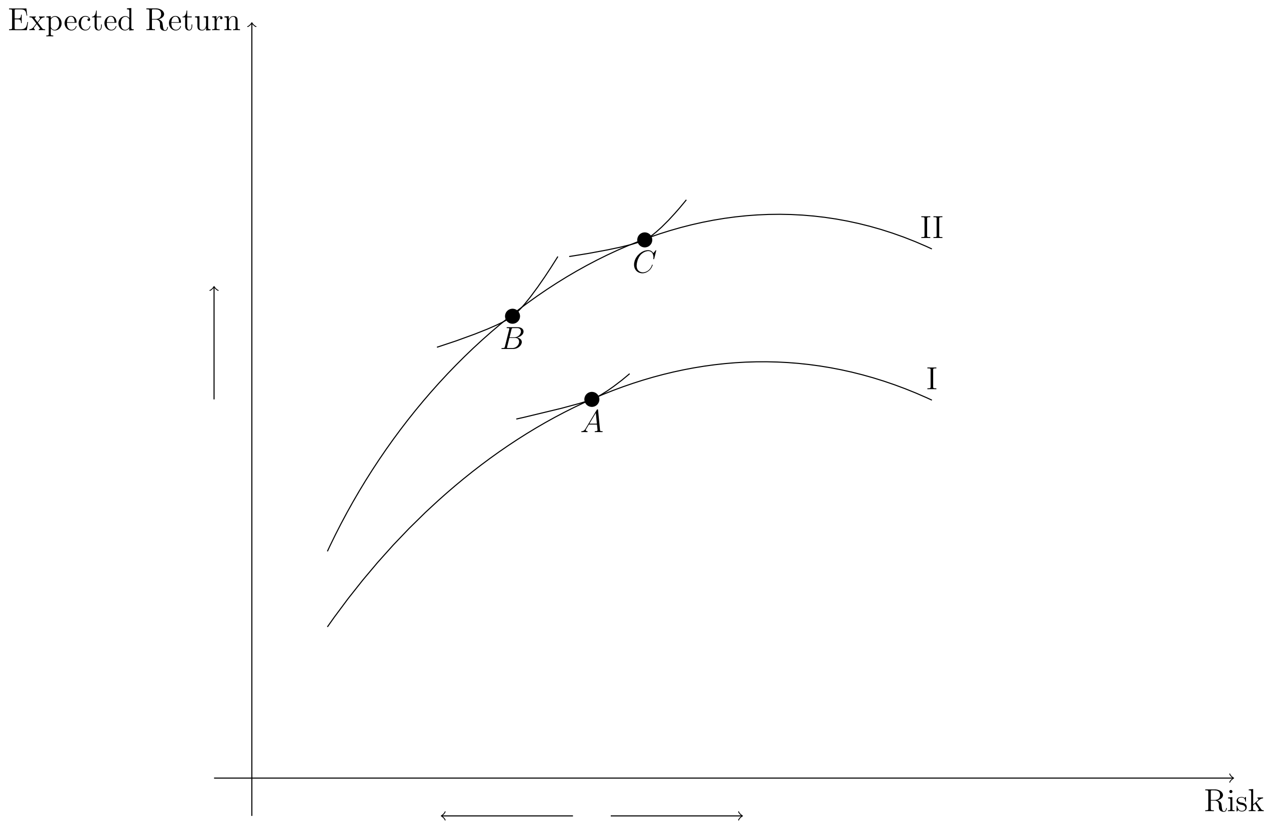
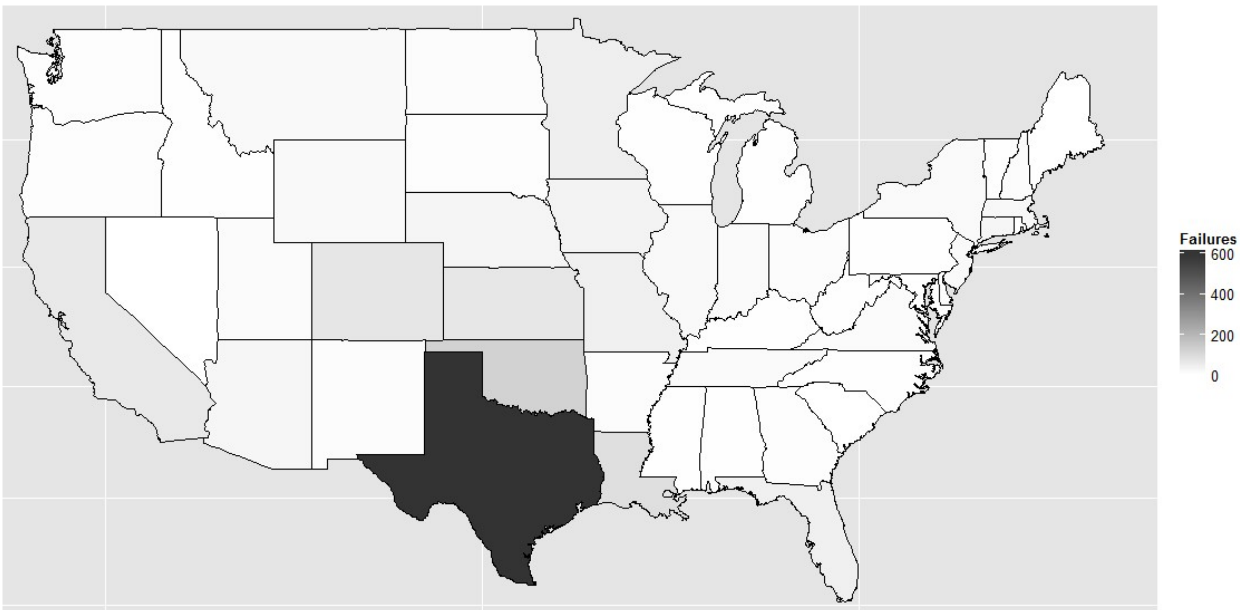


Figure 2: Heat Maps for U.S. Commercial Bank Failures

(a) 1985-1992



(b) 2008-2013

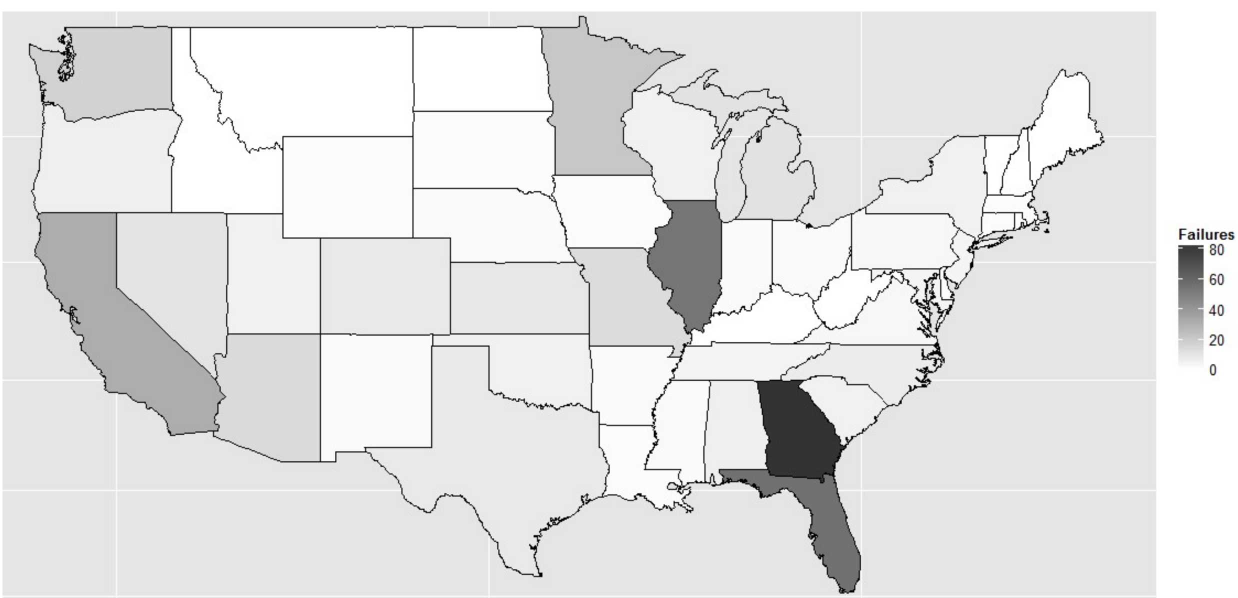
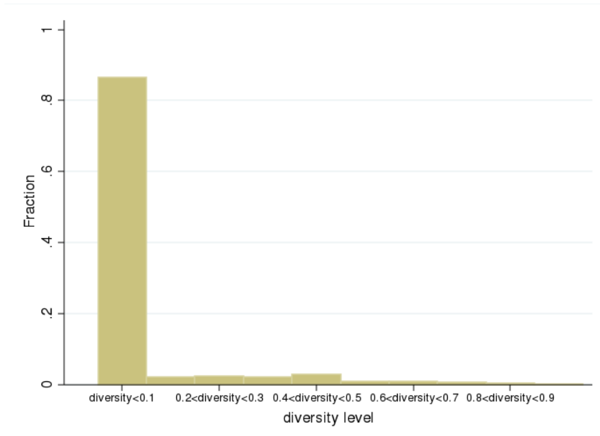
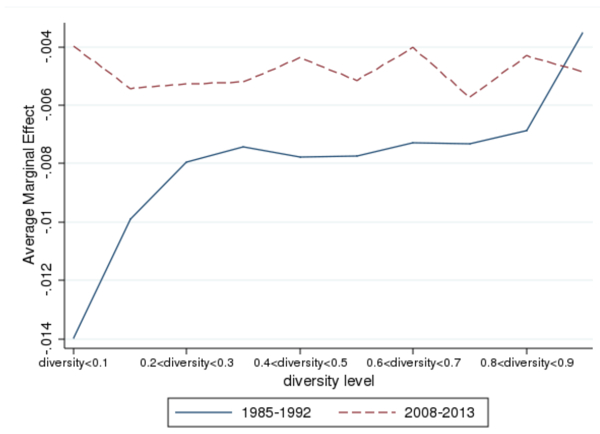


Figure 3: Analysis of Average Marginal Effects of *diverse* on Probability of Insolvency, by *diverse* Level

(a) Histogram of *diverse* Levels, 1985-1992



(b) Average Marginal Effects of *diverse* on Probability of Insolvency, by *diverse* Level



(c) Histogram of *diverse* Levels, 2008-2013