

What drives banks' geographic expansion? The role of locally non-diversifiable risk*

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Abstract

Why do some banks react to deregulation by expanding geographically while others do not? This paper examines this question using exogenous variation in locally non-diversifiable risk that banks face in their home state. As a measure of locally non-diversifiable risk we use data on damages arising from natural disasters in the U.S. Combining this data with information on the staggered deregulation in the 90s, we find that banks facing such risks expand significantly more into other states after deregulation than banks that do not face such risks. Only large banks are able to take advantage of deregulation, small banks are not. Finally, banks that do expand, do not necessarily seek to reduce their exposure to risk when expanding.

Keywords: banking, locally non-diversifiable risk, catastrophic risk, deregulation, geographic expansion

JEL Classification: G21, G28

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1 Introduction

There is a large literature examining whether the geographic expansion by banks increases or reduces risk (e.g., Goetz et al., 2015). One major challenge that this literature faces is that both risk taking and whether or not a bank responds to deregulation by geographically expanding are endogenous to the bank and may be driven by some common unobservable factor. Empirically, after deregulation, only some banks choose to open operations in other regions, while many do not and this choice may be interrelated in a myriad of ways with the choice of the bank how much risk to take. In this paper we take advantage of an exogenous source of locally non-diversifiable risk to the bank: local natural disasters. We combine this exogenous source of risk with the staggered process of banking deregulation in the U.S. during the 1990s in order to cleanly identify the motivation behind banks' geographic expansion activities.

The key findings are as follows: Banks facing a high level of non-diversifiable risk in their home market expand significantly more into other states than banks that face a low level of non-diversifiable risk. Using within-state county-level correlations of natural disasters, we further show that banks that face more opportunities for within-state diversification are less likely to expand out of state due to disaster risk. In addition, the effect of disaster risk on bank expansion is disproportionately stronger for larger banks. Small unitary banks, even when faced with high non-diversifiable risk, seem unable to take advantage of deregulation. Finally, we show that banks that face higher regional risk use the expansion opportunities to expand into regions with local risk that is positively correlated with the local risk in their home state. Hence, our results suggest that banks do not necessarily use geographic expansion to diversify risk, but rather seek out states with similar locally non-diversifiable risk. The findings are consistent with the idea that when expanding banks apply the locally gained expertise in managing certain types of risk to other areas with similar risks. The evidence may explain the mixed findings in the previous literature regarding geographic expansion and observed levels of risk in banks (e.g. Loutskina and Strahan, 2011; Goetz et al., 2015) .

Our paper is related to different strands of the literature. The theoretical and empirical literature on bank risk-taking strongly emphasizes the role of (geographic) diversification for banks' lending decisions and bank risk (Winton, 1997; Acharya et al., 2006; Winton, 2000; Loutskina and Strahan, 2011). For example, Loutskina and Strahan (2011)

show that if banks diversify geographically, their screening efforts and profits are lower, which makes them more vulnerable during the financial crisis of 2008-09. Goetz et al. (2015) analyze whether the geographic expansion of U.S. bank holding companies' assets affects their risk. By modeling the entry decisions of bank holding companies into other metropolitan areas using banking market liberalization as an instrument, they find that geographical expansion reduces the risk of multi-bank holding companies, although it does not reduce loan quality. While these papers provide evidence on the *consequences* of geographic expansion on bank risk, our paper explores the role of risk as a *determinant* of geographic expansion.

More generally, the paper contributes to the literature on the effects of banking deregulation in the U.S. For example, Keeley (1990), Jayaratne and Strahan (1998) and Gan (2004) show that liberalization of banking regulation during the 1970s and 1980s led to higher competition, lower charter values and subsequently higher risk-taking and profits of banks. Brook et al. (1998) provide evidence for beneficial consolidation in the banking industry following the act. Goetz et al. (2013) show that valuations of bank holding companies were negatively affected by the deregulation phase during the 1990s. Rice and Strahan (2010) find that relaxation of geographical restrictions on bank expansion in the 1990s led to lower loan rates for SMEs. In this literature, liberalization of banking regulation is primarily viewed as a cause for higher competition among banks in their home markets. We are interested in a complementary aspect of such deregulation, namely, why some banks expand geographically in response to deregulation and others do not, which helps us to better understand the likely consequences of geographic expansion for banks' ultimate risk exposure (see also Kroszner and Strahan, 1999, on the political factors that explain the timing of branching deregulation).

The paper also contributes to a growing body of literature that analyzes consequences of catastrophic risk and banking. Garmaise and Moskowitz (2009) use the 1994 Northridge earthquake in California to show that earthquake risk impacts credit markets through a more than 20 percent decreased provision of commercial real estate loans. Cortes and Strahan (2014) show that banks operating in many regions reallocate capital when local credit demand increases after natural disasters. Chavaz (2014) finds that lenders that had very concentrated portfolios in markets affected by the 2005 hurricane season increased lending through loan sales. Klomp (2014) shows that natural disasters decrease the sta-

bility of the banking sector by increasing the likelihood of bank failures. Lambert et al. (2014) find that banks that were exposed to Hurricane Katrina in 2005 react to the shock by increasing their risk-based capital ratios.

Our paper proceeds as follows: Section 2 describes the data used in this study. Section 3 presents our empirical model and our estimation results. Section 4 concludes.

2 Data

2.1 Sample description

The sample covers banks with a headquarter in the 48 continental states of the United States during the period 1994-2012. We exclude banks if the data is not available for all consecutive years, or if the headquarter location changes from one state to another during the sample period. We do not perform any further data cleaning. This leads to a sample covering between 12,095 banks in 1994 (5,770 banks in 2012) and 159,247 bank-year observations for our main regressions. We use bank-level data and not (consolidated) bank holding company data, because the regulatory change that we use for identification, i.e., the liberalization of geographic branching restrictions through the Riegle-Neal Act of 1994, primarily affected the bank level and not the bank holding company level.

2.2 Variables description

Disaster risk. The main contribution of this paper is to estimate the probability of expanding into another state after deregulation as a function of locally non-diversifiable risk. The proxy we use for a bank's disaster risk is the long-term disaster damage in the bank's business region over the period 1969 to 2012, denoted as DIS_i .

We calculate DIS_i in three steps: First, we determine the yearly damage by county in US\$ and scale it by a measure of economic activity. We therefore use over 20.000 individual records on property damages (measured in US\$) from the *Spatial Hazard Events and Losses Database for the United States* (SHELDUS) for the period 1969-2012. The database is provided by the *Hazards and Vulnerability Research Institute* at the University of South Carolina.¹ We scale these numbers by a county's yearly total personal income

¹Internet source: webra.cas.sc.edu/hvri.

(also measured in US\$), which is available from the *Bureau of Economic Analysis*.² For example, the standardized disaster damage we obtain for Orleans County in 2005 when Hurricane Katrina hit the region is 0.95. Thus, according to our measure, total property losses nearly equaled the total personal income of the population of Orleans County in 2005. The value we obtain for Los Angeles County in 1994 when the Northridge earthquake occurred is 0.0964.

Second, we need to identify how much individual banks operating in one or several counties may be affected by disaster damage. If a bank operates only in one county, our damage measure of bank i at year t , $dis_{i,t}$, equals the calculated property losses over total personal income of the respective county. For example, Santa Monica Bank (now part of U.S. Bank) had only branches in Los Angeles County in 1994, the year of the Northridge earthquake, and we assign a value $dis_{i,t}$ equal to the value of Los Angeles County in that year, i.e., 0.0964. If a bank has branches in more than one county, which is the case for the large majority of banks, we calculate $dis_{i,t}$ as the weighted county damage, using the bank's shares of deposits per county before the liberalization (as of 1994) as weights. The deposit data come from the FDIC's *Summary of Deposits* statistic, which shows the amount of deposits by branch and county for all U.S. banks since 1994.³ For example, Capital Bank had branches in Los Angeles County and Orange County in 1994, with a share of deposits of about two-thirds and one-third, respectively. Because there were no reported disaster damages in Orange county in 1994, Capital Bank gets a value for $dis_{i,t}$ equal to two-thirds of the disaster damages in Los Angeles County, i.e., 0.0662.

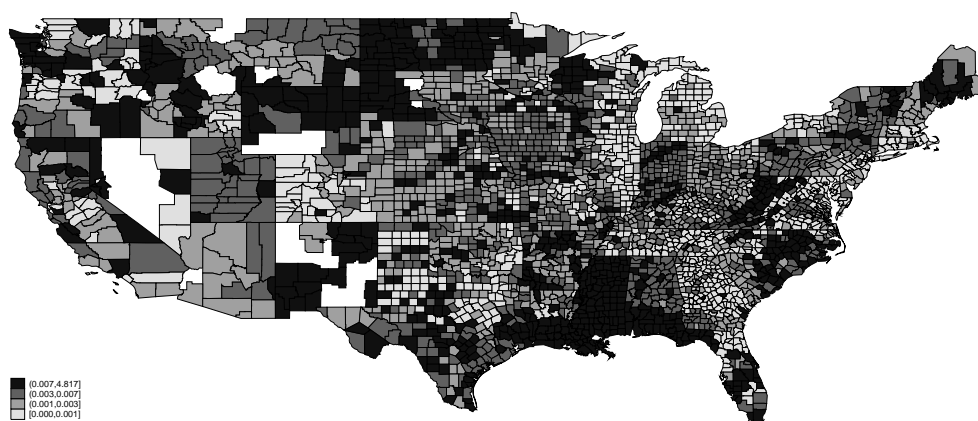
Finally, we calculate for each bank the disaster risk DIS_i as the long-term average over all $dis_{i,t}$ from 1969 to 2012. The distribution of DIS_i across the U.S. is illustrated in Figure 1 based on the banks' headquarter locations. As the figure shows, banks in some counties are facing on average only small disaster damages (light colors), while banks in other counties are facing high disaster damages (dark colors). Banks with headquarters in the U.S. Gulf Coast region near New Orleans (2005 Hurricane Katrina), in south Florida (frequent hurricanes) and in Los Angeles county (1994 Northridge earthquake) are among the banks with very high disaster risk DIS_i over our sample period.

As shown in Figure 2, the distribution of DIS_i is highly skewed. About 90% of all

²Internet source: www.bea.gov.

³Internet source: www2.fdic.gov/sod/.

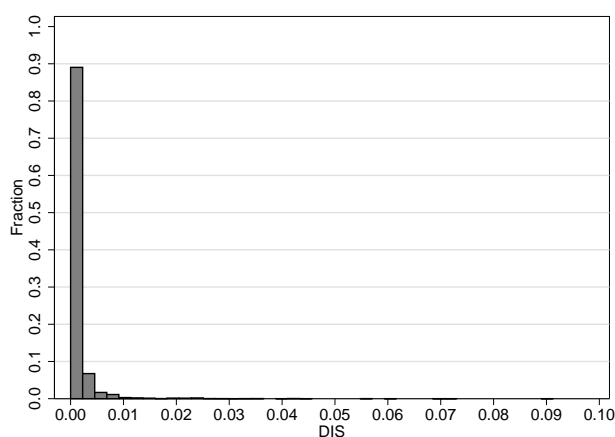
Figure 1: Damages from natural disasters by banking headquarter location



Notes: The figure shows average measures of DIS_i , which is calculated as the average yearly disaster damage over total income on county-level over the period 1969 to 2012, weighted by the bank's deposits in each county in 1994 (the year of the Riegle-Neal Act). The value of each county is the average over all banks with their headquarter in this county.

observations are about zero. This reflects that natural disasters represent rare events, which are nevertheless very relevant when they occur.

Figure 2: Distribution of DIS



Notes: The figure shows the distribution of disaster risk DIS_i , which is calculated as the average yearly disaster damage over total income on county-level over the period 1969 to 2012, weighted by the bank's deposits in each county in 1994 (the year of the Riegle-Neal Act).

Expansion opportunities. Banking in the U.S. was geographically restricted for a long time during the 20th century as a result of the McFadden Act of 1927 and other laws that attempted to address long-standing concerns about the concentration of financial

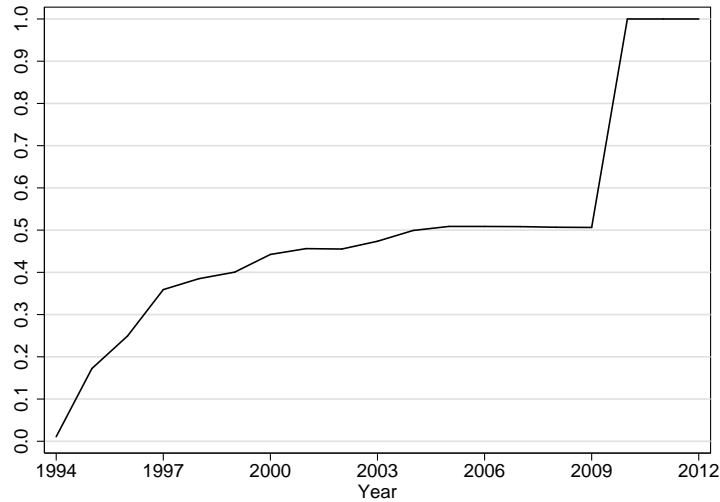
activity and worries that large banking organizations operating in multiple states could not be adequately supervised. Following a long period of high stability in the banking industry, many of these restrictions were abolished during the 1970s, 1980s and 1990s. In particular, intra-state banking was deregulated during the 1970s and 1980s, and the Riegle-Neal *Interstate Banking and Branching Efficiency Act* of 1994 (Riegle-Neal Act) removed many of the restrictions on opening bank branches across state lines. Following the Riegle-Neal Act of 1994, each state had to liberalized its banking market in some form, but there was much leeway how and when to do this. For example, states were allowed to curb liberalization by restricting entry based on the minimum age of institutions for acquisitions, *de novo* interstate branching, acquisitions of single branches, and statewide deposit caps on branch acquisitions. Hence, the timing and intensity by which each state opened its banking market differed widely between states (for details, see Johnson and Rice, 2008; Rice and Strahan, 2010). Finally, the Dodd-Frank Act of 2010 (Section 613) removed all restrictions to branch into any other state.

Following the literature, we use the staggered relaxation of geographic restrictions on branching across the U.S. to identify when banks had the opportunity to expand into other states. In particular, we use the information when a state for the first time allowed banks from other states to enter via *de novo* branches or acquisitions of single branches, based on the overview provided in Rice and Strahan (2010).

Next, we construct an “diversification opportunity index” (OPP) for each bank and year to approximate the extent of opportunities a bank has to expand into other states. For this index, we weight the information whether states allowed interstate branching with the average inverse distance between states. This index is higher when more states at a close distance to the banks’ home state allowed for interstate branching. We plot this index in Figure 3. We find that the average index rises to about 0.6 between 1994 and 2009 and then finally jumps to 1 when all restrictions were removed by the Dodd-Frank Act of 2010.

Geographic expansion. We use a measure for bank geographic expansion as dependent variable to explore banks’ expansion strategies following the Riegle-Neal Act of 1994. Figure 4 illustrates the situation for banks with headquarter locations in Louisiana (upper picture) and banks with headquarter locations in Colorado (lower picture). The figures confirm that distance is important for banks’ decisions where to open new branches. The

Figure 3: Expansion opportunity index



Notes: This figure shows the development of the expansion opportunity index. The year 1994 is when the Riegle-Neal Act was enacted and led to a deregulation of branching restrictions across the U.S., which nevertheless differed across state. The year 2010 is when all restrictions were removed through the Dodd-Frank Act.

role of disaster risk, which affects Louisiana more than Colorado, does not become clear yet from the figures.

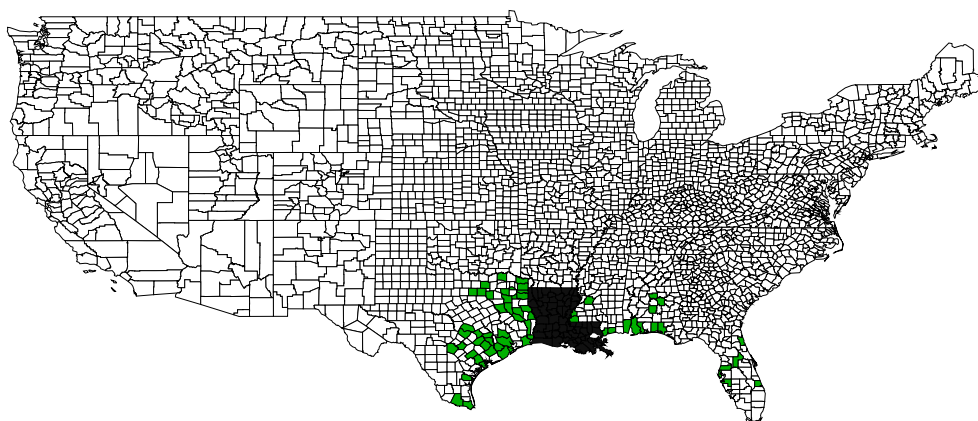
Our main variable for geographic expansion of banks is EXP , which measures the bank's share of deposits outside the bank's home state ("out-of-state deposit share"). The calculation is based on annual data since 1994 from the *Summary of Deposits* statistics of the FDIC.

Regional control variables. We use a set of state-level variables in order to control for regional economic differences and dynamics between states. In particular, we use differences in the Case-Shiller house price index⁴ on state level (ΔCS) and differences in state level GDP growth ($\Delta GROWTH$). Similar to the calculation of the expansion opportunity index, we weight ΔCS and $\Delta GROWTH$ with the average distance between states. We also use the log level of GDP in the bank's home state (GDP) and the bank's home state Case-Shiller house price index (CS) to control for developments of the economy in each state.

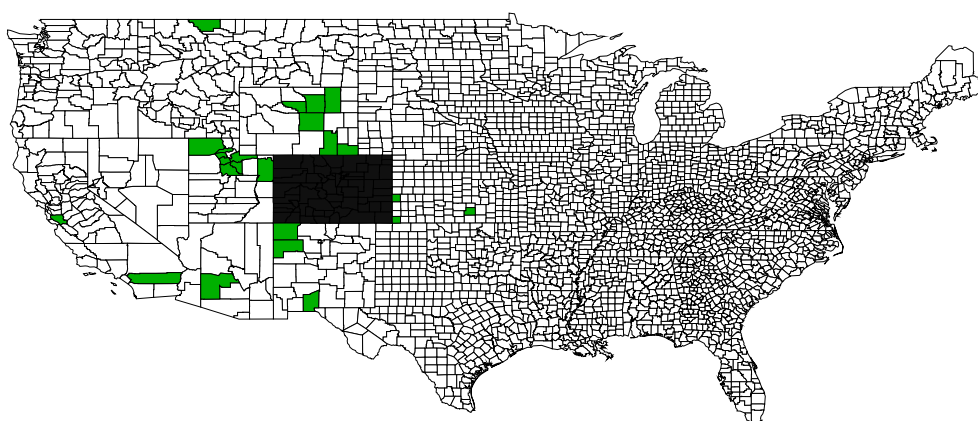
We also use the "branching restrictiveness index" from Rice and Strahan (2010) which

⁴See www.bea.gov.

Figure 4: Geographic expansion across U.S. counties



(a) Banks with headquarter locations in Louisiana



(b) Banks with headquarter locations in Colorado

Notes: Example state maps' description for some state with high/low long run damages. The upper picture (a) shows banks with a headquarter in Louisiana (black area) and the counties the banks have expanded between 1994 and 2012. The lower picture (b) shows banks with a headquarter in Colorado (black area) and the counties the banks expanded between 1994 and 2012.

takes values between 0 and 4 and indicate the degree of restrictions related to branching liberalization on the state level, where 0 is the least restrictive liberalization. In this study, we consider significant liberalization events that correspond to a value of 0 or 1 (LIB=1). This happened in seven states during the year 1995, in two states during 1996, in four states during 1997, and in 10 states between 1998 and 2005.⁵ State legislation that is relatively restrictive (index of 2 to 4) we classify as no significant liberalization (LIB=0). We further consider all years before a first liberalization step of a state as LIB=0. We also use VOL which is the per state volatility (standard deviation) of damages from

⁵In one state during 1998, in two states during 2000, in three states during 2001, in one state 2002, in two states during 2003, in one state during 2004, and in one state 2005.

natural disasters over personal income for each year between 1969 and 2012. This variable is suited to pick up within-state diversification opportunities with regard to risks from natural disasters for each bank.

Bank-level control variables. We further use year-end financial information on U.S. banks for the period 1994-2012, as provided by the Federal Deposit Insurance Corporation (FDIC).⁶ The database contains data from banks' *call reports* for all banks that are regulated by the FDIC. From this data we use the information whether a bank belong to a multi-bank holding company (MBHC), the size of the banks as the log of total assets (SIZE) and banks' total equity ratio (EQ).

An overview of all variables is provided in Table 1.

[Table 1 around here]

2.3 Summary statistics

Table 2 shows summary statistics for the full sample. Further, Table 3 provides summary statistics for the years 1994, the year when the Riegle-Neal Act was adopted, and Table 4 provides summary statistics for the year 2012, the last year of our sample period. All tables also include mean values separated for high-cat and low-cat banks, i.e., for banks with *disaster risk* above and below the median, respectively.

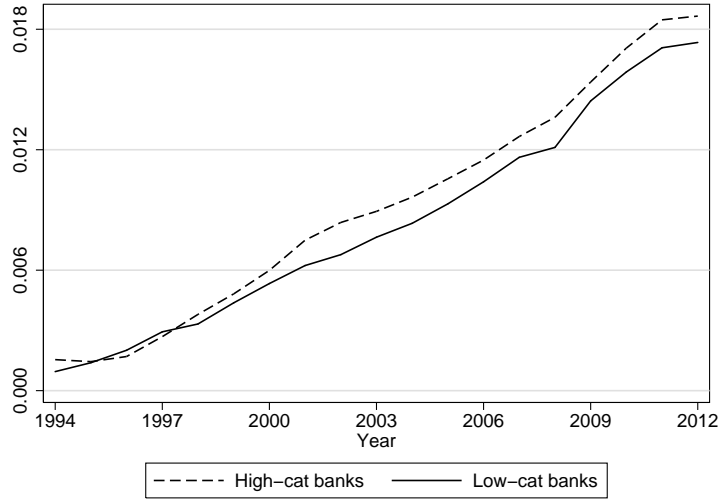
[Table 2, Table 3 and Table 4 around here]

Noteworthy from Tables 2, 3 and 4 we find that the average bank does not necessarily geographically expand: banks hold less than 1% of its deposits out-of-state. As we will see below this low degree of geographic expansion even after deregulation is in part explained by the fact that small community banks do not react to deregulation. Compared to 1994, this changes quite a lot since the average of out-of-state deposits in 2012 is around 2% with some banks having more than 45% of their deposits outside their home state. On average we find only small differences in means for the groups of low-cat and high-cat banks. Further, equity ratios and the average bank size increase between 1994 and 2012. Moreover, the share of banks belonging to a multi-bank holding company is about 22% over the sample period with a remarkable decrease of about 12 percentage points

⁶Internet source: www.fdic.gov/bank/statistical

between 1994 and 2012. Last, high-cat and low-cat banks seem not to differ very much regarding bank characteristics like size or risk and are operating in very similar economic surroundings.

Figure 5: Geographic expansion by banks' out-of-state deposit share



Notes: This figure shows the development of the share of out-of-state deposits per bank for high- and low-cat banks separately for the period 1994-2007. For illustrative purposes, we assign banks to the group of “high-cat banks” and to the group of “low-cat banks” if their catastrophic risk measure DIS_i is in the upper half or lower half of the sample, respectively.

As a first indication of the role of risks arising from natural disasters in banks' expansion decisions consider Figure 5. Figure 5 separates the development of banks' out-of-state deposits share for banks that are facing relatively high catastrophic, locally non-diversifiable risk (high-cat banks, above the median of DIS_i) and banks that are facing relatively low catastrophic, locally non-diversifiable risk (low-cat banks, below the median of DIS_i). While the out-of-state deposits share increases for all banks since 1994, the figure indicates that high-cat banks hold a higher share of out-of-state deposits since the late 1990s. This suggest that on average banks facing relatively high catastrophic risk expand more actively into other markets. We will examine whether this basic result is robust in a difference in differences setting and to a myriad of controls and fixed effects below.

3 Empirical model and results

3.1 Do banks facing locally non-diversifiable risk expand more?

Model. Our first set of analyses tests whether banks responded differently to the liberalization of the Riegle-Neal Act of 1994 in other states depending on the level of (catastrophic) non-diversifiable risks in their home markets. We estimate the following difference-in-difference model:

$$\begin{aligned} EXP_{it} = & \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \\ & + \gamma_1 \Delta CS_{st} + \gamma_2 CS_{st} + \gamma_3 \Delta GROWTH_{st} + \gamma_4 GDP_{st} \\ & + \gamma_5 LIB_{st} + \gamma_6 EQ_{it} + \gamma_7 SIZE_{it} + e_{it} \end{aligned} \quad (1)$$

EXP_{it} represents our measure of diversification, defined as a bank's share of deposits outside the bank's home market, i.e., the home state, for bank i in state s at year t . The variable OPP reflects the diversification opportunities on an annual basis for each bank in each state. The variable DIS indicates the long run average of natural disaster damages over personal income weighted with the bank presence in counties in 1994. We control for bank fixed effects ν_i and year fixed effects τ_t . We further introduce three regional control variables that vary over time t and states s . The variable ΔCS indicates differences in the development of the state-level Case Shiller house price index. Further, $\Delta GROWTH$ measures GDP growth differences between states. Both differences are weighted with the average inverse distance between states. We approximate by GDP the development of the economy of a bank's home state by log level of GDP and further control for housing price dynamics with each bank's home state Case Shiller house price index (CS). We further use EQ , which is a bank's total equity ratio, and the natural logarithm of total assets ($SIZE$) to account for time-varying bank characteristics. Finally, we use LIB to control for different intensities of liberalization in the banks' home states.

We are most interested in the differential effect β_2 , which tells us whether banks diversify relatively more or less with regard to their opportunities to branch into other states after 1994 conditional on the level of locally non-diversifiable risk they faced in the counties they were active in in 1994.⁷

⁷Note that the variable DIS drops out when we employ bank fixed effects because it is a constant measure per bank over time. In unreported regression we run a version of Equation (1) with time fixed

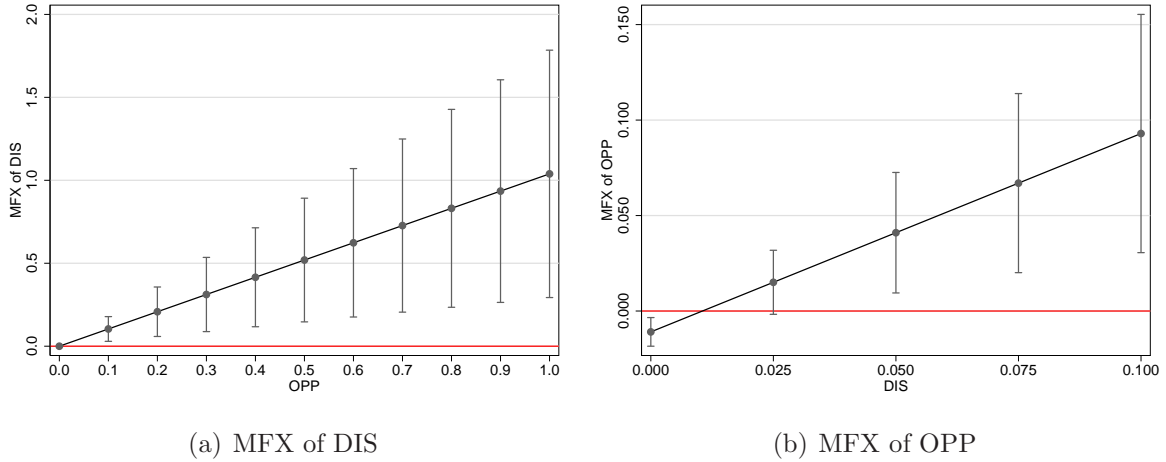
Results. Table 5 shows regression results for Equation (1). The second and third column then show results for the groups of high-cat banks and low-cat banks. In the second column we consider a bank a high-cat when the value of DIS_i is above median. In the third column we focus on a more extreme group with values of DIS_i above the 90% percentile. In all three versions β_2 come out positive and significant indicating that banks facing higher regional risk and have more expansion opportunities have higher shares of out-of-state deposits. Since the effect is more significant in the third column, our baseline result seems to be driven by banks in the top 10% of the distribution of DIS_i as indicated by Column 3.

[Table 5 around here]

Next, we consider marginal effects (and significance) of DIS on bank geographic expansion for values of the expansion opportunity index (OPP) between 0 and 1 in the left panel of Figure 6. This figure shows that the effect of DIS on out-of-state diversification activities by banks is increasing with expansion opportunities to enter other states via branching. For a value of OPP equals 0.5, the economic effect is around 0.5 which means that if DIS increases by one standard deviation (0.0033), the share of out of state deposits increases by $0.0033 \times 0.5 = 0.0017$, which means an increase of about 17 basis points. In terms of a mean value of EXP about 0.75%, this would mean a increase of about 23%. When we consider the effect of full liberalization after 2010, this would mean an increase of about 50%.

The other covariates in Table 5 come out in an intuitive way. We find that a growing home state economy makes out-of-state expansion less likely which might indicate that banks have ample investment opportunities in their home states. The variables ΔCS is negative and significant showing that house price differences matters for regional expansion of banks in that larger differences make expansion less likely. On the other hand, a larger house prices index in the banks' home states is associated with significant more expansion. $\Delta GROWTH$ is positive and significant showing that higher out-of-state deposits are associated with a better growing economy at home. This might be plausible in a sense that only banks in strong home markets, i.e., a strong basis can afford to enter regions out-of-state. We further show that larger banks and banks with higher equity ratios are effects only and show that our results are robust to this change.

Figure 6: MFX of DIS on EXP



Notes: This figure shows the conditional marginal effects of *DIS* on *EXP* depending on the level of the expansion opportunity Index (*OPP*). The graph corresponds to the regression results from Column 1 of Table 5. The vertical lines indicate the respective 95% confidence intervals.

more likely to expand out-of-state which again indicate that expansion is associated with a larger and sound base at home.

So far we have drawn inference about the effect of *DIS* on *EXP* conditional on expansion opportunities which is our main concern in this paper. We find that higher regional risks from natural disasters causes banks to increase their out-of-state deposits and that this effect is more pronounced if the banks have more opportunities to expand out-of-state after 1994. An alternative aspect of this nexus is the marginal effect of *OPP* on *EXP* conditional on the distribution of the long run average of scaled natural disaster damages. This effect is provided by the right graph of Figure 6. We find that for the lower part of the distribution of *DIS* there is no significant effect from *OPP* on *EXP* showing that for rather small, i.e., normal levels of disaster damages an increase of expansion opportunities does not lead to significant more out-of-state deposits. For values larger than 0.025 of *DIS* the marginal effect from *OPP* on *EXP* becomes significant at the 5% level. Regarding the economic effect we find that if we increase expansion opportunities by one standard deviation (roughly 0.25), banks that face rather high long term disaster damages of about 0.012 hold a higher share of out-of-state deposits of about 0.25 basis points, which accounts for an increase of about one third of the mean of *EXP* (0.0075).

Robustness. To challenge our results we run several robustness checks for our baseline regression and provide results in Table 6. First, in order to control more rigorously for demand effects we augment our baseline regression with state-year fixed effects. In Column 1 of Table 6 we report that including these additional fixed effects that pick up all of the remaining variation between states over time leaves our results intact. Second, following Goetz et al. (2015) we left out the financial crisis of 2007-08 and the time thereafter when the Dodd-Frank Act removed the remaining barriers for inter-state banking and branching and report results in Column 2 of Table 6. Again we find that this leaves our results unchanged. Third, results in Column 3 of Table 6 shows that leaving out the control variables does not change the size and significant level of the interaction effect either. Unreported, we also check different ways to cluster the standard errors (Petersen, 2009). We try two-way clustering on the bank and time dimension and interacted bank-time clustering. We also check the time dimension only and also variants with clustering on the state dimension. We find that clustering on the bank level and on the state level produce the most conservative standard errors and that all alternative variants make our results even slightly more significant.

The last column of Table 6 provide results for a version of the baseline regression in which we change the dependent variable. In Column 4 we use the logarithm of the US\$ amount of banks' out-of-state deposits instead of the share EXP . We find that the interaction effect is positive and significant which corroborates our baseline results and shows that our results so far are not driven by the denominator of EXP . Regarding the size of the coefficient we find an effect of roughly 61 which translates into an economic effect of a one standard deviation increase of DIS at a value of $OPP = 0.5$ as $61 \times 0.5 \times 0.0033 = 0.10$, an increase of about 10%.

[Table 6 around here]

3.2 Expansion and bank and regional characteristics

Model. Next, we explore whether bank and regional characteristics have an effect on bank behavior. In detail we check whether banks that belong to a multi-bank holding company (MBHC) or that are larger in asset size (LARGE, split of SIZE at the median value) act differently with regard to risk from natural disasters and opportunities to branch into other states. Further, we check whether liberalization due to the Riegle-Neal

Act of 1994 in the banks' home states (LIB) affects our results. Last, we look whether banks behave differently when they have diversification opportunities with respect to undiversifiable risk from natural disaster already available in their home states (VOL(p50), split at the median value of VOL). We interact each of the four variables with DIS and OPP:

$$\begin{aligned}
EXP_{it} = & \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \\
& + \beta_3 X_{it} + \beta_4 (OPP_{st} \times X_{it}) + \beta_5 (DIS_i \times X_{it}) + \beta_6 (DIS_i \times OPP_{st} \times X_{it}) \quad (2) \\
& + \gamma_1 \Delta CS_{st} + \gamma_2 CS_{st} + \gamma_3 \Delta GROWTH_{st} + \gamma_4 GDP_{st} \\
& + \gamma_5 LIB_{st} + \gamma_6 EQ_{it} + \gamma_7 SIZE_{it} + e_{it},
\end{aligned}$$

where X_{it} stands for MBHC, LARGE, LIB or VOL(p50).

Results. Results are shown Table 7.

[Table 7 around here]

According to the results in the first column of Table 7 we find that banks belonging to a multi-bank holding company are not those that drive our baseline result. Again, total marginal effects of DIS on EXP are hard to tell from the coefficients. We therefore provide conditional marginal effects in Figure 7. The upper left graph shows the interaction effect for both groups of banks. The lighter gray color indicate banks belonging to a multi-bank holding company. Both groups of banks shows positive conditional marginal effects over the whole range of the OPP variable but we find that the effects of DIS on EXP is not significantly different between both groups.

The second column of Table 7 shows whether larger banks (in the top half of the distribution of the log of total assets) act differently with regard to the expansionary behavior of small banks. We find again that DIS and the expansion index increase the out-of-state expansion of banks and that this effect is more pronounced for larger banks (see the upper right graph of Figure 7). The conditional marginal effect of DIS is statistically significant between large and small banks indicating that banks need a certain size in order to expand into other states.

Third, we test whether liberalization of banking market in the banks' home states has an additional effect on our baseline results. Therefore we interact DIS and the expansion

index with the LIB, which shows whether the bank’s home state liberalized its banking market significantly or not. The third column of Table 7 shows results for this setup and the lower left graph of Figure 7 shows the conditional marginal effect of *DIS* on banks’ expansion behavior over the whole range of the expansion index for both groups of banks. We find that those banks coming from states which liberalized significantly tend to be more active in going out of their home states. However, as the triple interaction term in Table 7 shows, this is not statistically significant. Put differently, pressure from competition that may arise when states liberalize their banking markets (e.g., Keeley, 1990) does not seem to be an additional factor in our analysis.

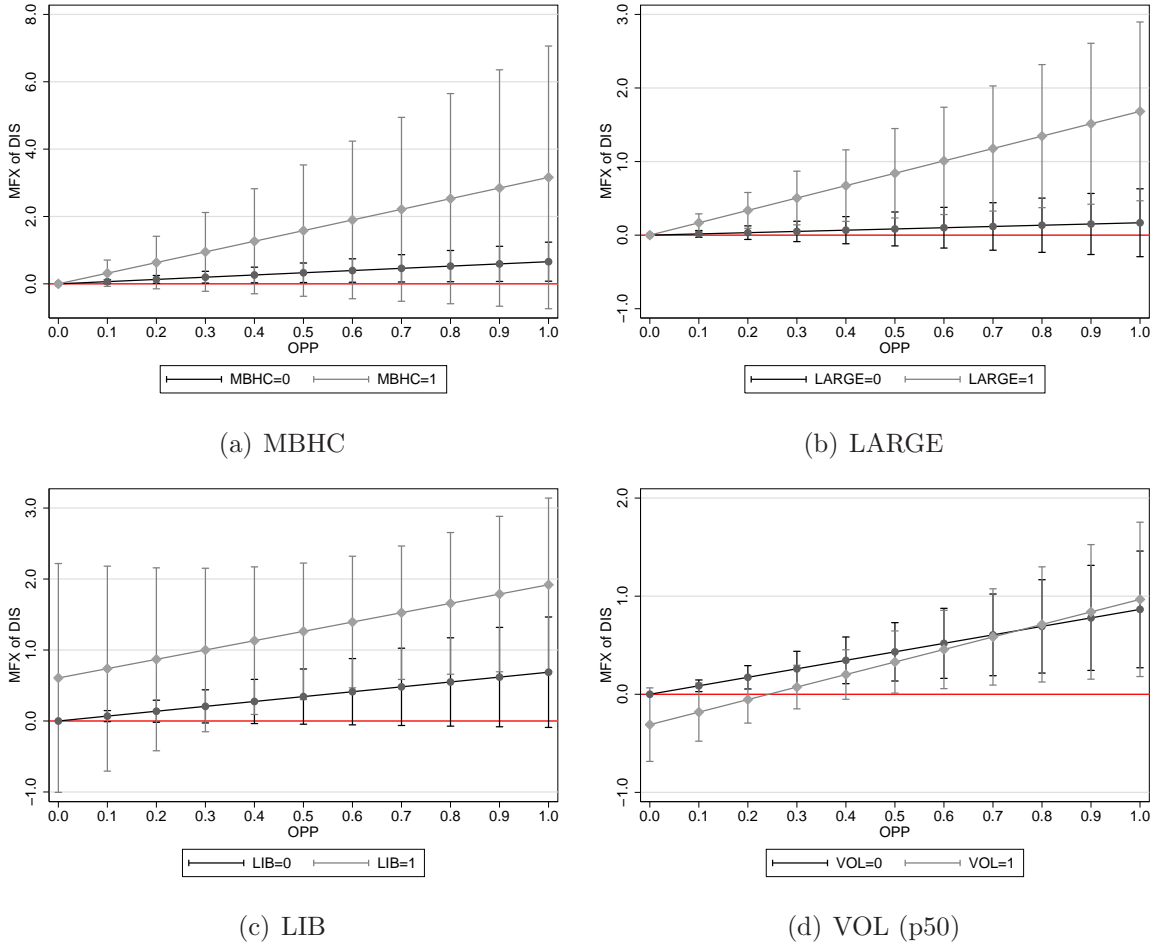
Last, we test whether diversification opportunities with regard to damages from natural disasters in the banks’ home state affect our results. If banks can diversify within their home state, the opportunity to expand into other states may be less valuable. We therefore interact *DIS* and the expansion index with VOL(p50), which results from the median split of the state specific standard deviation of damages from natural disaster over GDP over all counties for each year between 1969 and 2012. As indicates by the the lower right graph of Figure 7, banks that face less variation of damages from natural disaster in their home state (darker gray line) expand more into other states than banks that face a higher variation, i.e., potentially already have diversification opportunities in their home states. Again, we do not find this effect to be significantly different for both groups over the whole range of the OPP as indicated by the last column of Table 7.

3.3 Where do banks expand to?

In this section we explore the correlation of disaster risk between a bank’s home market and the bank’s new markets where it opened new branches following 1994.

Model. In this section we use CORR as the dependent variable. CORR is constructed in the following way: first we use the time series TS_i of damages from natural disasters over GDP that each bank would a faced when we consider only the counties the banks were active in 1994. Second, we also use the times series of damages from natural disasters over GDP for each $k = 1, \dots, K$ county TS_k . Third, we calculate for each bank all correlations between TS_i and TS_k . With this set of correlations we then calculate for each bank the average correlation (weighted by the inverse distance) with all counties outside each bank’s

Figure 7: MXF of DIS on EXP for bank and regional characteristics



Notes: This figure shows the conditional marginal effects of *DIS* on *EXP* depending on the level of the expansion opportunity Index (OPP) and four alternative dummies. The upper left graph shows marginal effects for banks that belong to a bank holding company (MBHC=1) or not (MBHC=0). The upper right graph shows marginal effects for large (LARGE=1) and small (LARGE=0) banks. The lower left graph shows marginal effects for a bank's home state liberalization (LIB=1 if de novo banking and/or acquisition of single branches was allowed, and LIB=0 otherwise). The lower right graph shows marginal effects for the median split of the volatility of damages from natural disaster for all counties in a state for the period 1969-2007 (VOL(p50)=1 for high volatility, and VOL(p50)=0 otherwise). The lighter gray lines indicate the development for the groups assigned with to 1. The darker gray line indicate the effects for the groups assigned to a 0. All graphs correspond to the regression results from Column 1 and 4 of Table 7. The vertical lines indicate the respective 95% confidence intervals.

home state which gives us a kind of benchmark correlation that is possible for each bank if it would expand out-of-state. Next, we calculate for each bank and year the actual average (inverse distance weighted) out-of-state correlation coming from the counties a bank decides to expand to. Last we calculate the difference between this observed yearly correlation and the benchmark correlation for each bank and year. For all banks who do

not expand in a particular year, this difference is zero. This variable $CORR$ now indicates whether a bank increases or decreases its correlations between disaster damages by its out-of-state expansion in each year, relative to a benchmark in which they randomly expand without any consideration of the relationship between disaster risk between their home region and the target region. We use the same regression model as in the previous section:

$$\begin{aligned}
CORR_{it} = & \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \\
& + \gamma_1 \Delta CS_{st} + \gamma_2 CS_{st} + \gamma_3 \Delta GROWTH_{st} + \gamma_4 GDP_{st} \\
& + \gamma_5 LIB_{st} + \gamma_6 EQ_{it} + \gamma_7 SIZE_{it} + e_{it}
\end{aligned} \tag{3}$$

Results. Results for $CORR$ as dependent variable are shown in Table 8. Figure 8 shows marginal effects of DIS .

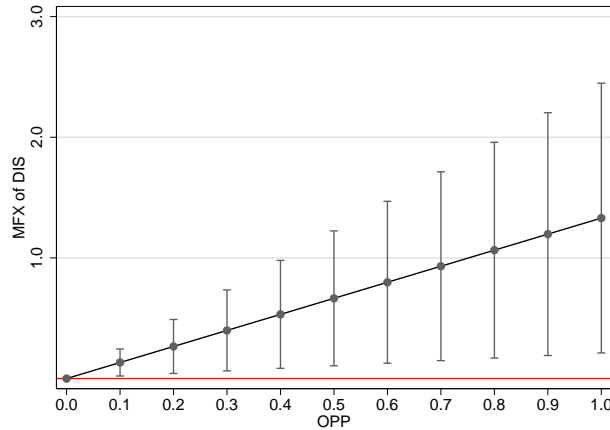
[Table 8 around here]

The first column shows that banks that face higher regional risks and have more opportunities to expand in other states do not use their expansion opportunities to expand into regions where local risk are uncorrelated to the risk in their home region. On the contrary, a one standard deviation increase of DIS for 50% expansion opportunities increases $CORR$ by 21 basis points. Given a mean value of $CORR$ about 0.005, the economic effect here is sizeable.

The second and third column of Table 8 show that when we use the median and 90% percentile splits for DIS , the results remain positive and significant showing that high-cat banks move into regions where locally non-diversifiable risk tends to be positively correlated with locally non-diversifiable risk in their home region. Overall, the results from this section suggest that banks did not take advantage of the increase in regional expansion opportunities that started in the 1990s in order to diversify locally non-diversifiable risk.

Correlations, bank and regional characteristics. A straightforward extension to explore the correlation results in more detail is to run a regression similar to Equation (3) in which we now analyse whether the effects of DIS on $CORR$ are further affected by regional and bank characteristics. We provide results in Table 9 and provide marginal effects for DIS again in a graphical form in Figure 9.

Figure 8: MFX of DIS on CORR



(a) MFX of DIS for CORR

Notes: This figure shows the conditional marginal effects of *DIS* on *CORR* depending on the level of the expansion opportunity Index (*OPP*). The graph corresponds to the regression results from Column 1 of Table 8. The vertical lines indicate the respective 95% confidence intervals.

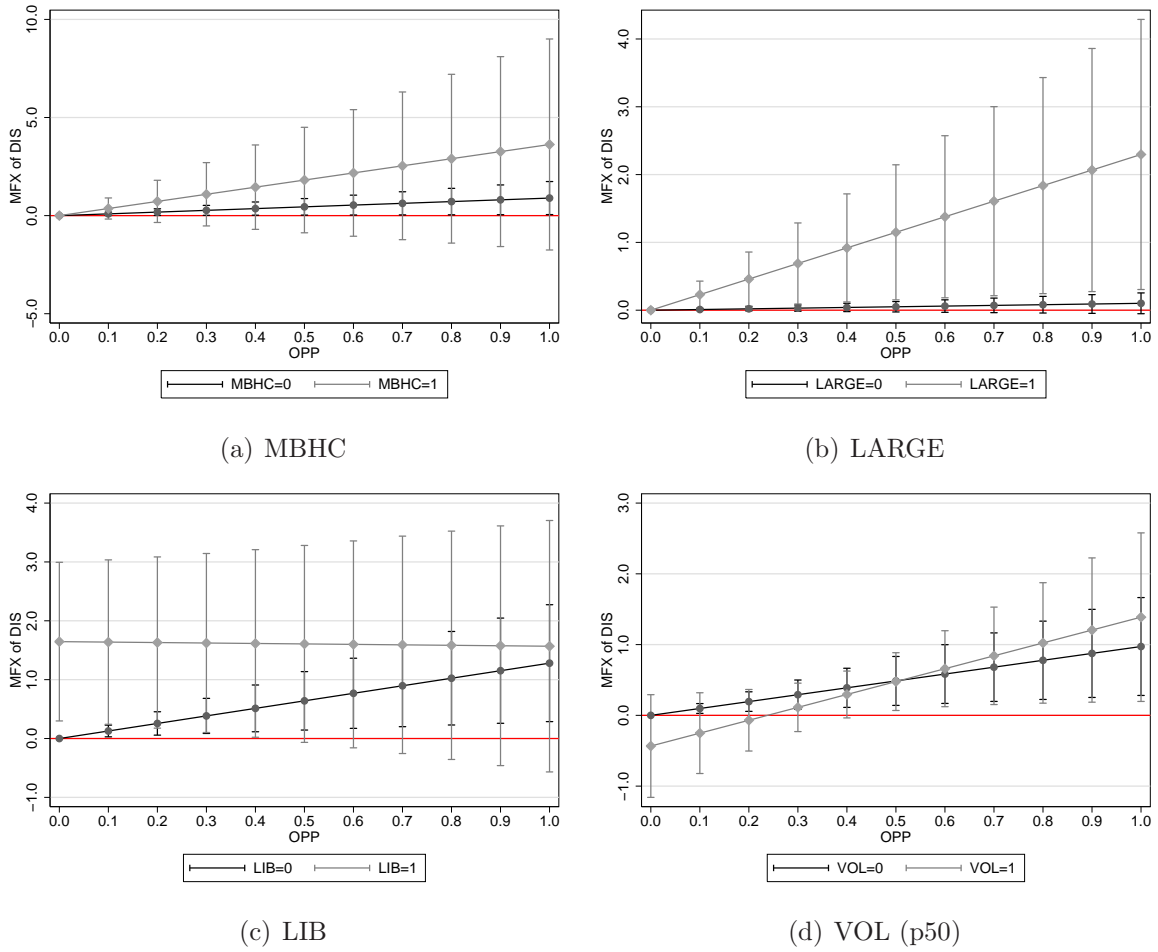
When we consider banks that belong to a multi-bank holding company we again find no significant differences between both groups of banks as shown in the upper left graph of Figure 9

When we turn to bank size, the upper right graph of Figure 9 shows that the correlation increasing effect of lifting geographic expansion restrictions is significantly more pronounced for large banks than small banks. Similar to our results in Section 3.2 we argue that banks need a certain size in order to expand into other regions. As it turns out, large banks that potentially can afford expansion benefit from this by significantly increase their correlation within disaster risks.

Next, we again consider liberalization of banking market in the banks' home states to differentiate between banks. The lower left graph of Figure 9 shows that we find our baseline correlation increasing effect of *DIS* with more expansion opportunities and also show that banks residing in less liberal states are catching up if provided with more expansion opportunities.

Last, in the lower right graph of Figure 9 we differentiate banks again with regard to their within-home state diversification opportunities. We find no significant differences between banks with more or less within-home state diversification opportunities.

Figure 9: MXF of DIS on CORR for bank and regional characteristics



Notes: This figure shows the conditional marginal effects of *DIS* on *CORR* depending on the level of the expansion opportunity Index (OPP) and four alternative dummies. The upper left graph shows marginal effects for banks that belong to a bank holding company (MBHC=1) or not (MBHC=0). The upper right graph shows marginal effects for large (LARGE=1) and small (LARGE=0) banks. The lower left graph shows marginal effects for a bank's home state liberalization (LIB=1 if de novo banking and/or acquisition of single branches was allowed, and LIB=0 otherwise). The lower right graph shows marginal effects for the median split of the volatility of damages from natural disaster for all counties in a state for the period 1969-2007 (VOL(p50)=1 for high volatility, and VOL(p50)=0 otherwise). The lighter gray lines indicate the development for the groups assigned with to 1. The darker gray line indicate the effects for the groups assigned to a 0. All graphs correspond to the regression results from Column 1 and 4 of Table 9. The vertical lines indicate the respective 95% confidence intervals.

4 Conclusion

To answer the question why some banks react to deregulation by expanding geographically while others do not, we use a quasi-natural experiment to investigate whether U.S. banks that face higher locally non-diversifiable risk from natural disasters expand more into other states after banking deregulation made this possible during the 1990s.

We find that banks that face a high level of non-diversifiable risk in their home states – measured by their exposure to damages from natural disasters – expand significantly more into other states than banks that face a low level of non-diversifiable risk. Moreover, banks that have more opportunities for within-state diversification are less likely to expand out of state due to disaster risk. Further, we find that only larger banks take advantage of deregulation. Finally, we show that the expansion of banks significantly increases their correlations of regional risk among those regions in which they are active. The results are consistent with the idea that banks move into regions where they can take advantage of expertise gained in their home state. In turn this suggests that the effect of geographic diversification on banks' risk taking is ambiguous: While the risks that banks face may even increase through geographic expansion, banks also may have more expertise in managing precisely these types of risk.

References

- Acharya, V., Hasan, I., Saunders, A., 2006. Should banks be diversified? Evidence from individual bank loan portfolios. *Journal of Business* 79, 1355–1412.
- Brook, Y., Hendershott, R., Lee, D., 1998. The gains from takeover deregulation: evidence from the end of interstate banking restrictions. *The Journal of Finance* 53, 2185–2204.
- Chavaz, M., 2014. Riders of the storm: Economic shock & bank lending in a natural experiment. Working Paper.
- Cortes, K., Strahan, P., 2014. Tracing out capital flows: How financially integrated banks respond to natural disasters. Working Paper.
- Gan, J., 2004. Banking market structure and financial stability: Evidence from the Texas real estate crisis in the 1980s. *Journal of Financial Economics* 73, 567–601.
- Garmaise, M., Moskowitz, T., 2009. Catastrophic risk and credit markets. *Journal of Finance* 64, 567–707.
- Goetz, M., Laeven, L., Levine, R., 2013. Identifying the valuation effects and agency costs of corporate diversification: Evidence from the geographic diversification of US banks. *Review of Financial Studies* 26, 1787–1823.
- Goetz, M., Laeven, L., Levine, R., 2015. Does the geographic expansion of bank assets reduce risk? *Journal of Financial Economics*, forthcoming.
- Jayaratne, J., Strahan, P., 1998. Entry restrictions, industry evolution, and dynamic efficiency: Evidence from commercial banking. *Journal of Law and Economics* 41, 239–73.
- Johnson, C. A., Rice, T., 2008. Assessing a decade of interstate bank branching. *Wash. & Lee L. Rev.* 65, 73.
- Keeley, M., 1990. Deposit insurance, risk and market power in banking. *American Economic Review* 80, 1183–1200.
- Klomp, J., 2014. Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability* 13, 180–192.

- Kroszner, R. S., Strahan, P. E., 1999. What drives deregulation? economics and politics of the relaxation of bank branching restrictions. *Quarterly Journal of Economics* 114, 1437–1467.
- Lambert, C., Noth, F., Schüwer, U., 2014. How do banks react to catastrophic events? Evidence from Hurricane Katrina. Working Paper 94, SAFE.
- Loutskina, E., Strahan, P., 2011. Informed and uninformed investment in housing: The downside of diversification. *Review of Financial Studies* 24, 1447–1480.
- Petersen, M., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22, 435–480.
- Rice, T., Strahan, P., 2010. Does credit competition affect small-firm finance? *Journal of Finance* 65, 861–889.
- Winton, A., 1997. Competition among financial intermediaries when diversification matters. *Journal of Financial Intermediation* 6, 307–346.
- Winton, A., 2000. Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending. mimeo.

Tables

Table 1: Variable description

Variable name	Description
DIS	Average disaster damages: The average property disaster damages over total personal income by bank for the period 1969 to 2012, using banks' summary of deposits as of 1994 as weights. Source: Own calculations based on SHELDUS, Bureau of Economic Analysis and FDIC Summary of Deposits.
EXP	Out-of-state expansion: Measured as a bank's share of deposits that the bank has outside its home state (where its headquarter is located).
OPP	Expansion opportunities: We consider a state open for entry by branching when it allowed either <i>de novo</i> interstate branching or acquisitions of single branches or both. We weight this information with the average distance between states and calculate for all banks with a headquarter in the same state an index on a yearly basis.
Δ CS	Differences in the Case-Shiller index: This variable reflects distance weighted differences between regional estate prices on state level. Our source for this index is the Federal Reserve Bank of St. Louis.
Δ GROWTH	Differences in GDP growth: This variable reflects distance weighted differences between GDP growth on county level. Our source for this index is the Bureau of Economic Analysis.
VOL	Volatility of damages from natural disasters: This variable reflects the standard deviation for natural disasters over GDP over all counties in a state for each year over the period between 1969 and 2012.
MBHC	Multi bank holding company: Indicates whether a bank belongs to a multi bank holding company (1) or not (0) in the year before liberalization took place.
LIB	Home state liberalization dummy: Indicates whether a bank's home state liberalized its banking market significantly. It is 1 if the index by Rice and Strahan (2010) is 0 or 1. The dummy is 0 when the index by Rice and Strahan (2010) is larger than 1.
EQ	Bank equity ratio: Indicates the ratio of banks' total equity ratio (FDIC code: eqv).
SIZE	Bank size: Indicates the natural logarithm of a bank's total assets (FDIC code: asset).
LARGE	Bank size dummy: Indicates whether a banks is in the top/bottom half of the distribution of log assets.
CORR	Correlation: The correlation between a bank's time series of damages from natural disasters over GDP coming from their business regions in 1994 and each other time series of damages from natural disasters for another county. CORR is the distance-weighted difference between the average actual out-of-state correlation and the average correlation between all counties out of state.
Log(out-of-state) deposits	Log amount of out-of-state deposits: Indicates the natural logarithm of the US\$ of all deposits per bank and year held outside the bank's home state.

Notes: See a detailed discussion of variable in Section 2.

Table 2: Summary statistics for the full sample period 1994-2012

	Mean	SD	1th	25th	75th	99th	High-cat	Low-cat
EXP	0.0075	0.0537	0.0000	0.0000	0.0000	0.2612	0.0079	0.0070
DIS	0.0012	0.0033	0.0000	0.0002	0.0011	0.0150	0.0023	0.0002
OPP	0.4791	0.2470	0.0000	0.3379	0.5748	1.0000	0.4921	0.4661
EQ	0.1069	0.0538	0.0529	0.0816	0.1182	0.2598	0.1058	0.1080
SIZE	11.6608	1.3605	9.0789	10.7489	12.3810	16.0384	11.6275	11.6941
MBHC	0.2254	0.4178	0.0000	0.0000	0.0000	1.0000	0.2181	0.2326
LIB	0.2427	0.4287	0.0000	0.0000	0.0000	1.0000	0.1896	0.2957
VOL	0.0298	0.0675	0.0006	0.0040	0.0249	0.1011	0.0384	0.0213
Δ CS	-0.2523	0.8801	-1.9267	-0.7330	0.0820	3.1562	-0.4409	-0.0638
Δ GROWTH	-0.0012	0.0237	-0.0527	-0.0147	0.0100	0.0586	-0.0002	-0.0022
GDP	12.4012	0.9543	10.0042	11.8070	13.1326	14.3800	12.3504	12.4519

Notes: This table shows summary statistics for the full sample period 1994 to 2012. The last two columns show mean values for high-cat and low-cat banks. See Table 1 for a detailed description of all variables.

Table 3: Summary statistics for the year 1994

	Mean	SD	1th	25th	75th	99th	High-cat	Low-cat
EXP	0.0012	0.0235	0.0000	0.0000	0.0000	0.0000	0.0015	0.0009
DIS	0.0011	0.0030	0.0000	0.0002	0.0010	0.0121	0.0021	0.0002
OPP	0.0105	0.0389	0.0000	0.0000	0.0000	0.1787	0.0072	0.0136
EQ	0.0977	0.0471	0.0471	0.0755	0.1087	0.2267	0.0970	0.0984
SIZE	11.2155	1.2864	8.8735	10.3751	11.8348	15.6172	11.1601	11.2687
MBHC	0.2548	0.4358	0.0000	0.0000	1.0000	1.0000	0.2424	0.2667
LIB	0.0679	0.2517	0.0000	0.0000	0.0000	1.0000	0.0454	0.0895
VOL	0.0304	0.0700	0.0006	0.0040	0.0249	0.1011	0.0397	0.0214
Δ CS	-0.0910	0.4012	-0.7330	-0.3915	0.1446	1.1421	-0.1990	0.0128
Δ GROWTH	0.0033	0.0220	-0.0464	-0.0056	0.0176	0.0465	0.0059	0.0009
GDP	11.9776	0.9168	9.6188	11.4193	12.7529	13.7154	11.9238	12.0292

Notes: This table shows summary statistics for the year 1994. The last two columns show mean values for high-cat and low-cat banks. See Table 1 for a detailed description of all variables.

Table 4: Summary statistics for the year 2012

	Mean	SD	1th	25th	75th	99th	High-cat	Low-cat
EXP	0.0180	0.0812	0.0000	0.0000	0.0000	0.4713	0.0187	0.0173
DIS	0.0013	0.0036	0.0000	0.0002	0.0011	0.0203	0.0024	0.0002
OPP	1.0000	0.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
EQ	0.1133	0.0502	0.0393	0.0919	0.1242	0.2518	0.1128	0.1138
SIZE	12.1224	1.3203	9.6293	11.2391	12.8155	16.3850	12.1106	12.1346
MBHC	0.1319	0.3384	0.0000	0.0000	0.0000	1.0000	0.1283	0.1355
LIB	0.3712	0.4832	0.0000	0.0000	1.0000	1.0000	0.3082	0.4359
VOL	0.0291	0.0611	0.0008	0.0051	0.0249	0.1011	0.0369	0.0210
Δ CS	-0.3974	0.9866	-1.4932	-0.9441	-0.3868	3.1562	-0.6068	-0.1821
Δ GROWTH	0.0032	0.0283	-0.0400	-0.0098	0.0062	0.1844	0.0084	-0.0022
GDP	12.6017	0.9165	10.5634	11.9687	13.3039	14.5136	12.5473	12.6576

Notes: This table shows summary statistics for the year 2012. The last two columns show mean values for high-cat and low-cat banks. See Table 1 for a detailed description of all variables.

Table 5: Out of state diversification

Dependent variable:	EXP		
	(1)	(2)	(3)
OPP	-0.0109** (0.0046)	-0.0111** (0.0046)	-0.0104** (0.0045)
OPP × DIS	1.0388*** (0.3804)		
OPP × Dummy for high-cat banks (p50)		0.0036* (0.0021)	
OPP × Dummy for high-cat banks (p90)			0.0095** (0.0037)
ΔCS	-0.0164*** (0.0033)	-0.0161*** (0.0033)	-0.0164*** (0.0033)
CS	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
ΔGROWTH	0.0181*** (0.0068)	0.0187*** (0.0069)	0.0179*** (0.0068)
GDP	-0.0224*** (0.0071)	-0.0232*** (0.0071)	-0.0227*** (0.0071)
EQ	0.0661*** (0.0105)	0.0662*** (0.0105)	0.0662*** (0.0105)
Size	0.0235*** (0.0021)	0.0235*** (0.0021)	0.0235*** (0.0021)
LIB	0.0010 (0.0010)	0.0009 (0.0010)	0.0010 (0.0010)
Constant	-0.0225 (0.0827)	-0.0130 (0.0832)	-0.0192 (0.0829)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	159247	159247	159247
Banks	12095	12095	12095
Adj. R2	0.0699	0.0695	0.0697

Notes: This table shows regression results for Equation (1). Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively. See Table 1 for a detailed description of all variables.

Table 6: Robustness

Dependent variable:	EXP			Log(out-of-state deposits)
	(1)	(2)	(3)	(4)
OPP	-0.1862** (0.0921)	0.0003 (0.0042)	-0.0125** (0.0049)	-0.2761 (0.1747)
OPP \times DIS	0.8250** (0.3710)	1.1132* (0.5690)	0.9985** (0.3901)	59.1120*** (17.8963)
Δ CS	0.0820 (0.0559)	-0.0148*** (0.0030)		-0.9937*** (0.1687)
CS	-0.0007 (0.0004)	0.0001*** (0.0000)		0.0091*** (0.0015)
GDP	0.3455** (0.1633)	-0.0294*** (0.0074)		-1.0568*** (0.2694)
EQ	0.0678*** (0.0107)	0.0582*** (0.0086)		2.8642*** (0.4042)
Size	0.0238*** (0.0021)	0.0196*** (0.0022)		1.0624*** (0.0620)
LIB	0.1390** (0.0709)	0.0008 (0.0009)		0.1055** (0.0441)
Δ GROWTH		0.0159** (0.0062)		1.0469*** (0.2527)
Constant	-4.2794** (1.8855)	0.1065 (0.0855)	0.0006 (0.0004)	-1.0245 (3.2108)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Year \times State FE	Yes	No	No	No
Observations	159247	128404	159568	159247
Banks	12095	12095	12128	12095
Adj. R2	0.0820	0.0529	0.0242	0.1018

Notes: This table shows regression results for Equation (1). Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively. See Table 1 for a detailed description of all variables.

Table 7: The role of bank and regional characteristics

Dependent variable:	EXP			
	(1)	(2)	(3)	(4)
OPP	-0.0154*** (0.0046)	-0.0196*** (0.0047)	-0.0096** (0.0045)	-0.0104** (0.0046)
OPP × DIS	0.6582** (0.2958)	0.1684 (0.2352)	0.6872* (0.3969)	0.8651*** (0.3035)
MBHC × OPP	0.0221*** (0.0043)			
MBHC × OPP × DIS	2.5029 (2.0124)			
LARGE × OPP		0.0253*** (0.0023)		
LARGE × OPP × DIS		1.5135** (0.6628)		
LIB			-0.0010 (0.0015)	
LIB × OPP			0.0018 (0.0026)	
LIB × DIS			0.6063 (0.8225)	
LIB × OPP × DIS			0.6260 (1.1643)	
VOL				0.0007 (0.0006)
VOL × OPP				-0.0016 (0.0012)
VOL × DIS				-0.3095 (0.1912)
VOL × OPP × DIS				0.4116 (0.3718)
ΔCS	-0.0171*** (0.0033)	-0.0103*** (0.0033)	-0.0155*** (0.0032)	-0.0161*** (0.0033)
CS	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
ΔGROWTH	0.0196*** (0.0068)	0.0085 (0.0069)	0.0174** (0.0069)	0.0180*** (0.0068)
GDP	-0.0230*** (0.0071)	-0.0019 (0.0070)	-0.0241*** (0.0071)	-0.0224*** (0.0071)
EQ	0.0627*** (0.0102)	0.0092 (0.0065)	0.0663*** (0.0105)	0.0661*** (0.0105)
Size	0.0230*** (0.0020)		0.0235*** (0.0021)	0.0235*** (0.0021)
LIB	0.0010 (0.0010)	0.0000 (0.0010)		0.0009 (0.0010)
Constant	-0.0108 (0.0830)	0.0052 (0.0844)	-0.0005 (0.0830)	-0.0221 (0.0827)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	159247	159247	159247	159247
Banks	12095	12095	12095	12095
Adj. R2	0.0742	0.0342	0.0705	0.0700

Notes: This table shows regression results for Equation (2). Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively. See Table 1 for a detailed description of all variables.

Table 8: Expansion and regional correlations

Dependent variable:	CORR		
	(1)	(2)	(3)
OPP	-0.0106*	-0.0108*	-0.0098*
	(0.0059)	(0.0059)	(0.0059)
OPP \times DIS	1.3301**		
	(0.5704)		
OPP \times Dummy for high-cat banks (p50)		0.0045**	
		(0.0019)	
OPP \times Dummy for high-cat banks (p90)			0.0111***
			(0.0040)
Δ CS	-0.0275***	-0.0272***	-0.0275***
	(0.0051)	(0.0051)	(0.0051)
CS	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Δ GROWTH	0.0075	0.0082	0.0073
	(0.0062)	(0.0063)	(0.0062)
GDP	-0.0136**	-0.0146**	-0.0140**
	(0.0065)	(0.0065)	(0.0065)
EQ	0.0063	0.0064	0.0064
	(0.0062)	(0.0062)	(0.0062)
Size	0.0066***	0.0067***	0.0066***
	(0.0011)	(0.0011)	(0.0011)
LIB	0.0052***	0.0052***	0.0052***
	(0.0011)	(0.0011)	(0.0011)
Constant	0.0436	0.0555	0.0476
	(0.0798)	(0.0799)	(0.0799)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	159247	159247	159247
Banks	12095	12095	12095
Adj. R2	0.0146	0.0139	0.0142

Notes: This table shows regression results for Equation (3). Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively. See Table 1 for a detailed description of all variables.

Table 9: The role of bank and regional characteristics for correlations

Dependent variable:	CORR			
	(1)	(2)	(3)	(4)
OPP	-0.0118** (0.0059)	-0.0137** (0.0059)	-0.0084 (0.0058)	-0.0089 (0.0060)
OPP × DIS	0.8946** (0.4298)	0.1014 (0.0782)	1.2803** (0.5066)	0.9728*** (0.3529)
MBHC × OPP	0.0061 (0.0040)			
MBHC × OPP × DIS	2.7305 (2.7755)			
LARGE × OPP		0.0095*** (0.0022)		
LARGE × OPP × DIS		2.1955** (1.0199)		
LIB			-0.0006 (0.0016)	
LIB × OPP			0.0091*** (0.0026)	
LIB × DIS			1.6461** (0.6874)	
LIB × OPP × DIS			-1.3583* (0.7365)	
VOL				0.0016** (0.0007)
VOL × OPP				-0.0042*** (0.0015)
VOL × DIS				-0.4335 (0.3702)
VOL × OPP × DIS				0.8483 (0.6802)
ΔCS	-0.0277*** (0.0051)	-0.0254*** (0.0051)	-0.0249*** (0.0050)	-0.0268*** (0.0051)
CS	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
ΔGROWTH	0.0080 (0.0062)	0.0051 (0.0062)	0.0056 (0.0062)	0.0078 (0.0061)
GDP	-0.0142** (0.0064)	-0.0074 (0.0064)	-0.0132** (0.0064)	-0.0136** (0.0065)
EQ	0.0050 (0.0061)	-0.0100* (0.0058)	0.0065 (0.0062)	0.0063 (0.0062)
Size	0.0064*** (0.0011)		0.0066*** (0.0011)	0.0066*** (0.0011)
LIB	0.0052*** (0.0011)	0.0049*** (0.0011)		0.0051*** (0.0011)
Constant	0.0526 (0.0785)	0.0477 (0.0799)	0.0431 (0.0781)	0.0441 (0.0797)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	159247	159247	159247	159247
Banks	12095	12095	12095	12095
Adj. R2	0.0156	0.0136	0.0152	0.0148

Notes: This table shows regression results for Equation. Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively. See Table 1 for a detailed description of all variables.