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Conference Paper

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

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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

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. 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. We further show that banks take advantage of deregulation in other states by reducing their exposure to disaster damages. 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 by reducing their exposures to these risks at the same time. 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 4 presents our empirical model and our estimation results. Section 5 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 further clean the data for missing data in all the variables we employ. We do not perform any further data cleaning or corrections. This leads to a sample covering between 11,926 banks in 1994 (5,644 banks in 2012) and 156,139 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 (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.

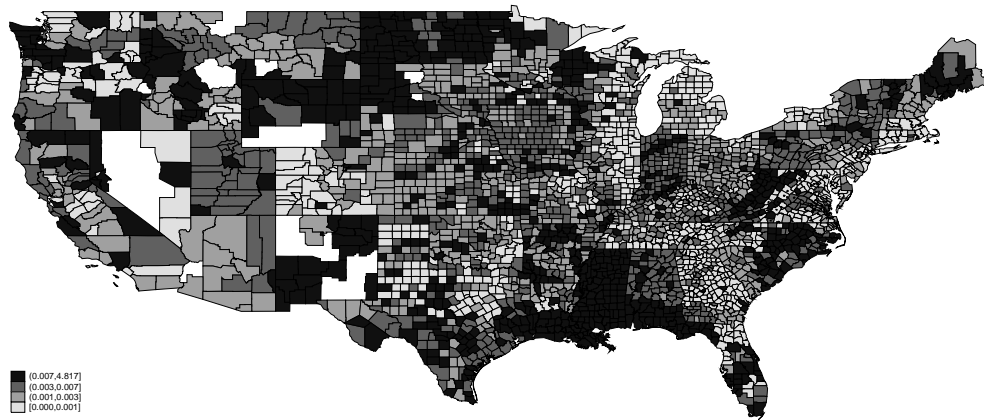
Finally, we calculate for each bank the disaster risk DIS_i as the long-term average over all $dis_{i,t}$ from 1969 to 2012. The distribution of DIS_i across the U.S. is illustrated in Figure 1 based on the banks’ headquarter locations. As the figure shows, banks in some counties are facing on average 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.

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

²Internet source: www.bea.gov.

³Internet source: www2.fdic.gov/sod/.

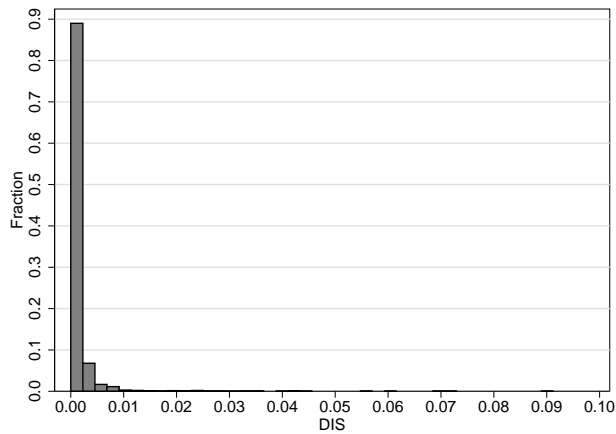
Figure 1: Damages from natural disasters by banking headquarter location



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.

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

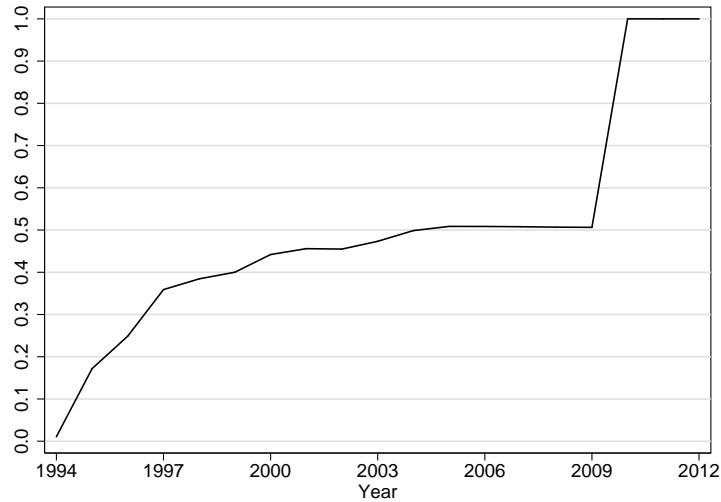
activity and worries that large banking organizations operating in multiple states could not be adequately supervised. Following a long period of high stability in the banking industry, many of these restrictions were abolished during the 1970s, 1980s and 1990s. In particular, intra-state banking was 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 0.5 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.

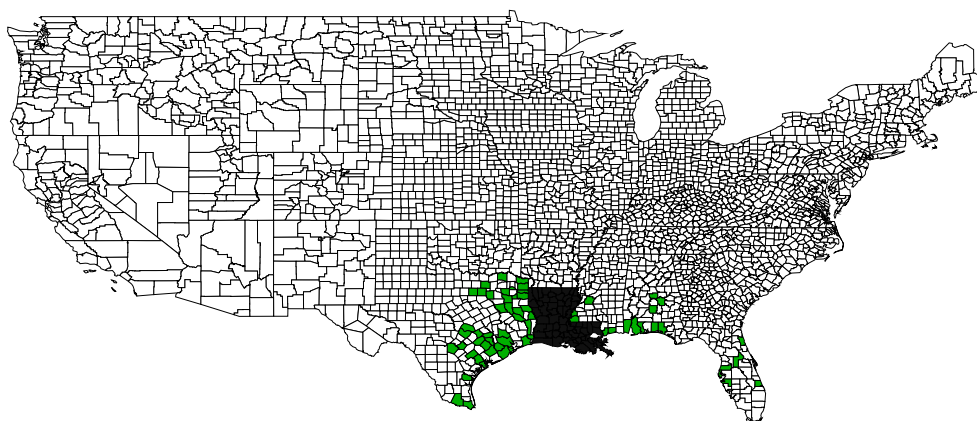
Our main variable for geographic expansion of banks is EXP , which measures the bank’s share of deposits outside the bank’s home state (“out-of-state deposit share”). The calculation is based on annual data since 1994 from the *Summary of Deposits* statistics of the FDIC.

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 (DCS) and differences in state level GDP growth (DGROWTH). Similar to the calculation of the expansion opportunity index, we weight DCS and DGROWTH 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.

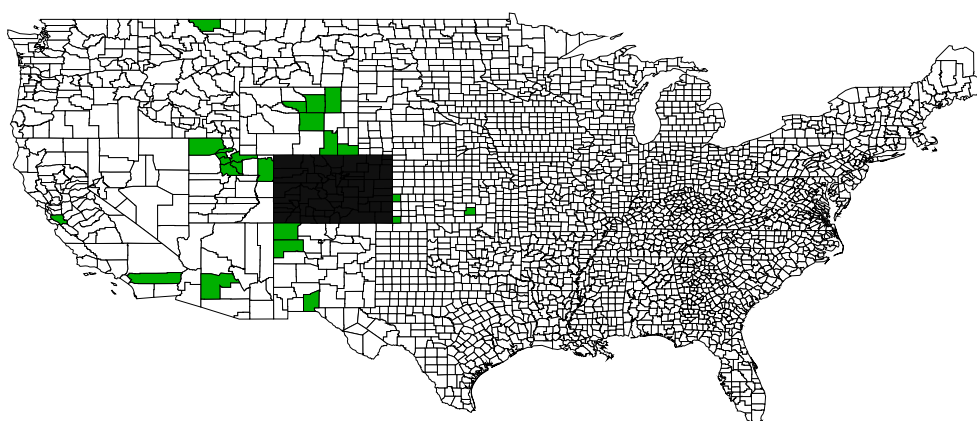
We also use the “branching restrictiveness index” from Rice and Strahan (2010) which takes values between 0 and 4 and indicate the degree of restrictions related to branching

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.

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 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

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 for each bank.

Last, we also want to control for within-state diversification opportunities for banks with respect to disaster risk. To do this we calculate VOL which represents the yearly standard deviation of damages from natural disaster for each state. To account for regional differences, we weight each damage with the county level of GDP.

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) or to holding company that spreads over more than one state (MSBHC), the size of the banks as the log of total assets (Size), banks' total equity ratio (EQ), banks cash holdings relative to total assets (Cash) and banks' profitability by their return over assets (ROA). Finally, we use Mean distance as a measure to control the average distance of the network of branches for each bank and year. We therefore calculate the distance between each county a bank collects deposits to the bank's home county and weight the average value of distance per year by the summary of deposits for each county.

A detailed explanation of variables we use in this paper is provided in Table 1.

[Table 1 around here]

2.3 Summary statistics

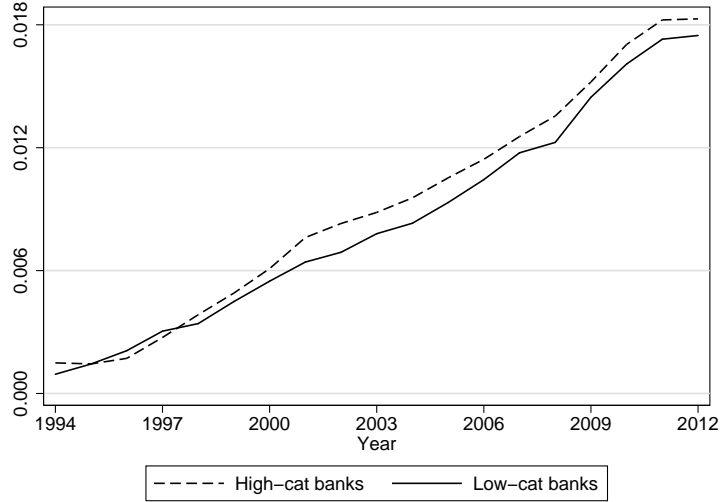
Table 2 shows summary statistics for the full sample for the period from 1994-2012.

[Table 2]

Noteworthy from Table 2 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.

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

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 Initial disaster effects for banks

Before analyzing the combined effects from liberalization and natural disasters on banks' out-of-state expansion decision, we first have to make sure that natural disaster have an impact on the banks in our sample. To show this we run fixed effects regressions investigate

whether the yearly, summary of deposits weighted, damages from natural disasters scaled by county GDP on the bank level dis_{it} affect bank risk:

$$Risk_{it} = \nu_i + \tau_t + dis_{it} + \sum_k \eta_k Bank_{kit} + \sum_j \gamma_j State_{jst} + \epsilon_{it} \quad (1)$$

$Risk_{it}$ is thereby a short-hand for different risk proxies for bank i in state s in the year t . To approximate bank risk we use NPA, which is the ratio of non-performing assets over total assets and the Z-score, the ratio of the sum of banks' return over assets and the equity ratio both divided by the standard deviation of returns over assets. The Z-score is regarded as a measure for bank stability since it captures the loss absorbency capacity of a bank's equity. Additionally we also use the three mentioned components of the Z-score on the left-hand side of Equation (1).

Moreover, we control for several factors in Equation (1). First, we include banks fixed effects ν_i and year fixed effects τ_t . Second, we add bank specific variables to control for size and liquidity but also the mean distance to the bank's home county of all counties a bank is active in (weighted by the summary of deposits from each county) and the expansion opportunities of each bank. Third, we control for state-specific factors such as the level of liberalization according to (Rice and Strahan, 2010), the standard deviation of natural disaster damages per state, the state level of GDP, the states' Case-Shiller index and the distance weighted differences of the Case-Shiller index and GDP growth to all other states.

Our results in Table 3 show that a higher yearly disaster risk that banks experience through their presence in different counties leads to significant higher non-performing asset ratio and to a lower Z-score, which means to a significant less stable bank. On an economic basis this means that a shift by one standard deviation, which means a shift from zero damages to the 95th percentile, leads to a 5 basis points shift in the ratio of non-performing assets and a 5% decrease of the Z-score. The last three columns of Table 3 show that this decreasing effect of yearly disaster damages on Z-scores come from a decrease in banks' equity and an increase in the volatility of banks' profitability. Our results that yearly disaster damages have an effect on bank risk are very robust as we show in an online appendix that we find similar results for regressions with lagged right-hand side variables and for a variant of Equation (1) without additional covariates. From

this preliminary analysis we draw the conclusion that natural disasters matter for banks since they potentially destroy customer’s collateral and thereby make bank business more difficult.

4 Empirical model and results

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

Model. Our first set of main 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 model:

$$EXP_{it} = \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \quad (2)$$

$$+ \sum_k \eta_k Bank_{kit} + \sum_j \gamma_j State_{jst} + \epsilon_{it}$$

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 six regional control variables that vary over time t and states s . The variable DCS indicates differences in the development of the state-level Case Shiller house price index. Further, $DGROWTH$ 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). Additionally, we control for a bank’s home state level of liberalization by LIB which is a dummy variable indicating a high level of liberalization and also include VOL which is the state-specific yearly standard deviation of disaster damages. We further use EQ , which is a bank’s total equity ratio, $Cash$ as the ratio of banks’ cash holding over total assets and the natural logarithm of total assets ($Size$) to account for time-varying bank characteristics. Last, we

include Mean distance which is the average distance between the banks' home counties and all counties each bank collects deposits weighted by the sum of these deposits.

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.

Results. Table 4 shows regression results for Equation (2). We run several variants of Equation (2) with different levels of fixed effects and control variables. The first column shows results for the most basic version without any fixed effects and control variables. Here, β_2 comes out positive and significant indicating that banks facing higher regional risk and have more expansion opportunities have higher shares of out-of-state deposits. This effect stays significant when we gradually add more control variables. We regard the results from Column 4 as our baseline results since here bank and year fixed effects and all control variables are added to the model.⁷ Again we find a significant and positive interaction term β_2 of similar size as in Column 1. The last two columns corroborates our results since our results stay robust when we further add state-year fixed effects (Column 5) to control more rigorously for demand effects or use only damages up to 1994 for the calculation of *DIS* to counter concerns about our forward looking measure of long term disaster risks. By showing that our results are robust when we use only damages up to 1994 we also make sure that damages from Hurricane Katrina, which have been outstanding for the South-East of the U.S. (Lambert et al., 2014), are not driving our results.

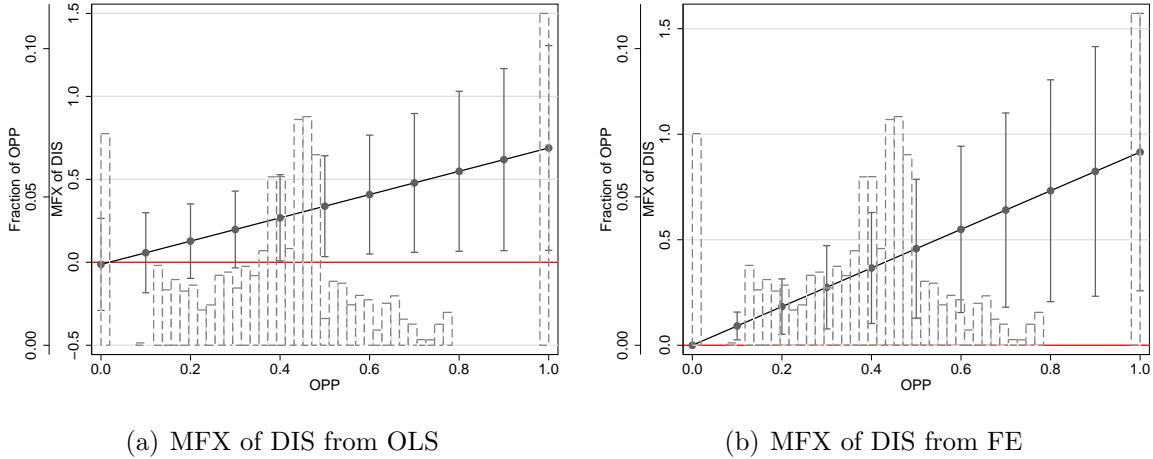
[Table 4 around here]

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. We shows these for each regression at the bottom of Table 4 and in Figure 6 which displays the marginal effects of *DIS* for Column 1 and 4 of Table 4. Both graphs of Figure 6 show 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 0.43 (median value), the economic effect is around 0.4 which means that if *DIS*

⁷Note that we cannot identify the single term of *DIS* in regressions with bank fixed effects.

increases by one standard deviation (0.0033), the share of out of state deposits increases by $0.0033 \times 0.4 = 0.0013$, which means an increase of about 13 basis points. In terms of a mean value of EXP about 0.75%, this would mean a increase of about 17%. When we consider the effect of full liberalization after 2010, this would mean an increase of about 40%.

Figure 6: MFX of DIS conditional on OPP



Notes: This figure plots marginal effects of DIS on EXP conditional on the level of OPP. The marginal effects in the left graph comes from a regression without any fixed effects or control variable while the right graph shows the marginal effects from a fully-specificity regression. Both graphs also include the distribution of OPP indicates at the second y-axis.

The other covariates in Table 4 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 DCS 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. DGROWTH is positive and significant showing that higher out-of-state deposits are associated with a better growing economy at home compared to the alternatives out-of-state. 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 more likely to expand out-of-state which again indicate that expansion is associated with a larger and sound base at home. Moreover, banks' cash holdings seem to be unimportant besides all the other variables but our results also show that more profitable banks are less likely to go out-of-state. Further, we

find that the volatility of disaster damages on the state level are not significant for the expansion decision of banks in our baseline results. The results in Column 4 also indicate that banks located in states with higher levels of liberalization are more like to expand out-of-state. This might indicate that competitive pressure at home drives banks into going out-of-state. Last, we find that banks that are more widely spread geographically are also this that are more likely to hold deposits out-of-state.

Robustness. To challenge our results we run several robustness checks for our baseline regression and provide results in Table 5. First, we use the natural logarithm of out-of-state deposits instead of the ratio to total deposits and show that this leaves our results intact. 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 24 for the median of expansion opportunities which translates into an economic effect of a one standard deviation increase of *DIS* at a value of as $24 \times 0.0033 = 0.08$, an increase of about 8%. Second, we change the way we measure long term disaster damages. So far we use the mean value for the period 1969-2012. In Column 2 of Table 5 we use the standard deviation instead which comes closer to the interpretation of risk from natural disaster. We find that the β_2 coefficient is still positive and significant showing that banks that face more volatile long term disaster damages are more likely to expand out-of-state. Third, 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 5. Again we find that this leaves our results unchanged. Fourth, results in Column 4 of Table 5 show that if we also check different ways to cluster the standard errors (Petersen, 2009) and try out two-way clustering on the bank and time dimension which does not change our results. Fifth, the last column shows that our results also hold when we only consider commercial banks, the majority of banks in the U.S.

[Table 5 around here]

4.2 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 a multi-state bank holding company (MSBHC) or that are larger in asset size (Size(D), split at \$250 million) act differently with regard to risk from natural disasters and opportunities to branch into other states. Further, we check whether banks behave differently when they have diversification opportunities with respect to undiversifiable risk from natural disaster already available in their home states (VOL(D), split at the median value of VOL). We interact each of the four variables with DIS and OPP:

$$\begin{aligned}
 EXP_{it} = & \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \\
 & + \beta_3 X_{it} + \beta_4 (OPP_{st} \times X_{it}) + \beta_5 (DIS_i \times X_{it}) + \beta_6 (DIS_i \times OPP_{st} \times X_{it}) \quad (3) \\
 & + \sum_k \eta_k Bank_{kit} + \sum_j \gamma_j State_{jst} + \epsilon_{it}
 \end{aligned}$$

where X_{it} stands for Size(D), MBHC, MSBHC and VOL(D).

Results. Results are shown Table 6.

[Table 6 around here]

According to the results in the first column of Table 6 we find that larger banks act differently with regard to the expansionary behavior of small banks (those with average total assets below \$250 million). Note that we will only provide marginal effects for *DIS* in the following. We provide all coefficients in the tables in the online appendix. Here, we provide marginal effects for *DIS* conditional on the 25th, 50th and 75th percentile of *OPP* or for full opportunities for both groups (0 for small banks, 1 for large 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. 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. Also, the economic effect increases. When we consider *OPP* at the median level we find that a one standard deviation increase of *DIS* increases out-of-state deposits by 16 basis points, an increase of about 21%.

In the second column of Table 6 we find that banks belonging to a multi-bank holding company are not those that drive our baseline result. Both groups of banks shows positive conditional marginal effects over the whole range of the *OPP* variable but those are only significant for the group of small banks. However, we find that the effects of *DIS* on *EXP* is not significantly different between both groups.

Third, we find that the split of banks into those belonging to multi-bank holding companies that spread over states and those that do not is more telling. The marginal effects in the second column of Table 6 for *DIS* are positive and significant for both groups but more pronounced for the multi-state group.

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 $VOL(D)$, 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 indicated in the last column of Table 6 this difference is not important for the expansion behavior of banks. The marginal effect of *DIS* is positive and significant for both groups of banks but do not differ over the range of *OPP*.

4.3 Effects on disaster risk and volatility

This section explores how banks' exposure to disaster risk change between 1994-2012 due to expansion opportunities and long term disaster risks bank face. We therefore use our baseline regression setup from Equation (2) but change the dependent variable in two ways. First, in order to investigate how the exposure to disaster damages change with the expansion behavior of banks we calculate *DISY* which represents the long term exposure to disaster risk that changes with the yearly change of counties the banks hold their deposits in. In detail we calculate the long term disaster damage per bank as we do for *DIS* but repeat this for each year and thereby use the respective counties a bank collects deposits from for each year to calculate the average weighted damage from disaster risk on the bank level using county disaster damages between 1969-2012. With this procedure we end up with a measure of disaster risk that changes each year for each bank and thereby reflects how the long term exposure to disaster risk changes with the change in

the summary of deposits for each bank and year. Second, we repeat this procedure but instead of using the long term average of disaster risk we use the standard deviation over the period 1969-2012 ($SD(DISY)$). We report marginal effects for DIS on both variables conditional on OPP in Table 7.

[Table 7 around here]

We find that the effect of DIS on both variables is negative and significant for the whole range of expansion opportunities. Thereby, the results of Table 7 indicate that banks that have higher long term disaster damages evaluated at the spread of the summary of deposits from 1994 take advantage of expansion opportunities and decrease their exposure to disaster damages and achieve a lower volatility of the long term disaster damages they face.

4.4 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 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 their 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:

$$CORR_{it} = \nu_i + \tau_t + \beta_1 OPP_{st} + \beta_2 (DIS_i \times OPP_{st}) \quad (4)$$

$$+ \sum_k \eta_k Bank_{kit} + \sum_j \gamma_j State_{jst} + \epsilon_{it}$$

Results. Results for CORR as dependent variable are shown in Table 8 in which we again show only marginal effects and provide the full set of coefficients in an online appendix. Table 8 has the same structure as Table 4.

[Table 8 around here]

The result that is robust through all columns of Table 8 is 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 the median value of expansion opportunities increases CORR by 19 basis points for the baseline regression in Column 4. Given a mean value of CORR about 0.005, the economic effect here is sizeable.

Correlations, bank and regional characteristics. A straightforward extension to explore the correlation results in more detail is to run a regression similar to Equation (4) in which we now analyze whether the effects of *DIS* on *CORR* are further affected by regional and bank characteristics. We provide results in Table 9.

When we consider bank size, we find 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 4.2 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.

When we turn to banks that belong to a multi-bank holding company we again find no significant differences between both groups of banks though the effect is significant for the banks not belonging to a multi-bank holding company. Again, we find positive and significant effects for banks that are part of multi-state bank holding companies and the

other banks but this time the effect is significantly large for those banks being associated with this multi-state bank holding structure.

Last, we differentiate banks again with regard to their within-home state diversification opportunities. We find that banks with more within-home state diversification opportunities tend to increase their correlations significantly but over the whole range of *OPP* it seems that this difference is only slightly significant.

5 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, only larger banks take advantage of deregulation. Finally, we show that the expansion of banks significantly decreases banks' exposure to disaster damages and further find an increase in the correlations of regional risk among those regions in which banks 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.

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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.
DIS(94)	Average disaster damages before 1994: The average property disaster damages over total personal income by bank for the period 1969 to 1994, 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.
DIS(y)	Yearly disaster damages: The average property disaster damages over total personal income by bank for each year between 1994 and 2012, using banks' summary of deposits from each year as weights. Source: Own calculations based on SHELDUS, Bureau of Economic Analysis and FDIC Summary of Deposits.
DISY	: This variable represents the change in the average long term property disaster damages for each bank that comes from yearly changes in the composition of the summary of deposits. In detail we first use the summary of deposits from 1994 and calculate the weighted long term average of disaster damages per bank as if the bank stays in the counties from 1994 until 2012. Then we repeat this calculation for each year between 1994 and 2012 and use the respective summary of deposits to calculate this value for each bank for each year.
SD(DISY)	Volatility of : This variable represents the change in the standard deviation of the average long term property disaster damages for each bank that comes from yearly changes in the composition of the summary of deposits. In detail we first use the summary of deposits from 1994 and calculate the weighted long term standard deviation of disaster damages per bank as if the bank stays in the counties from 1994 until 2012. Then we repeat this calculation for each year between 1994 and 2012 and use the respective summary of deposits to calculate this value for each bank for each year.
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.
DCS	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.
DGROWTH	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.

Table 1: Variable description continued

Variable name	Description
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.
MSBHC	Multi-state bank holding company: Indicates whether a bank belongs to a multi bank holding company that is active in more than one state (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).
NPA	Non-performing assets: Indicates the ratio of banks' total non-performing assets over total assets (FDIC code: XX).
ROA	Return over assets: Indicates the ratio of banks' returns over total assets (FDIC code: roa).
SD(ROA)	Standard deviation of RoA: Indicates eight quarter rolling standard deviation of banks' return over assets.
Z-score	Banks' Z-score: The Z-score is a measure of the loss absorbing capacity of banks' equity. It is calculates as the: $(EQ+ROA)/SD(ROA)$. A higher Z-score indicates a more stable bank.
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.
Mean distance	Mean distance between a bank's counties: This variable is calculates as the mean distance between a bank's home county to all the other counties the bank is active in as indicates by a positive value of the summary of deposits. The variable is weighted by the banks' summary of deposits for each county.

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

Table 2: Summary statistics

	Mean	SD	Percentiles					
			1st	25th	75th	90th	95th	99th
EXP	0.008	0.054	0.000	0.000	0.000	0.000	0.000	0.262
DIS	0.001	0.003	0.000	0.000	0.001	0.003	0.004	0.015
DIS(94)	0.001	0.003	0.000	0.000	0.001	0.002	0.004	0.009
DIS(y)	0.002	0.026	0.000	0.000	0.000	0.001	0.002	0.030
VOL(DIS)	0.006	0.021	0.000	0.001	0.005	0.014	0.021	0.104
MBHC	0.183	0.387	0.000	0.000	0.000	1.000	1.000	1.000
MSBHC	0.061	0.240	0.000	0.000	0.000	0.000	1.000	1.000
DISY	0.001	0.003	0.000	0.000	0.001	0.003	0.004	0.015
SD(DISY)	0.006	0.019	0.000	0.001	0.004	0.013	0.021	0.082
CORR	0.005	0.057	-0.042	0.000	0.000	0.000	0.000	0.237
OPP	0.445	0.259	0.000	0.291	0.530	1.000	1.000	1.000
NPA	0.052	0.196	0.000	0.012	0.065	0.117	0.164	0.313
EQ	0.107	0.050	0.054	0.082	0.118	0.150	0.175	0.256
SD(ROA)	0.003	0.008	0.000	0.001	0.003	0.006	0.009	0.024
Z-score	4.121	0.963	1.206	3.602	4.753	5.223	5.499	6.019
Mean distance	9.951	46.298	0.000	0.000	7.293	20.744	38.610	136.438
VOL	0.007	0.030	0.000	0.000	0.004	0.011	0.023	0.094
DGROWTH	0.000	0.022	-0.055	-0.011	0.011	0.027	0.037	0.052
DCS	-0.107	0.626	-1.279	-0.477	0.133	0.423	0.984	2.262
CS	249.644	93.992	130.020	189.410	287.040	358.860	429.620	622.160
GROWTH	12.394	0.953	10.004	11.800	13.129	13.701	13.927	14.380
Size	11.657	1.355	9.086	10.749	12.374	13.321	14.054	16.036
Cash	0.060	0.059	0.008	0.030	0.067	0.114	0.161	0.305
LIB	0.313	0.464	0.000	0.000	1.000	1.000	1.000	1.000

Notes: This table shows summary statistics for all variables we use in our analysis. See Table 1 for a detailed description of all variables.

Table 3: Initial effects of yearly disaster damages

Dependent variable:	NPA (1)	Z-score (2)	RoA (3)	EQ (4)	SD(RoA) (5)
DIS(y)	0.0293* (0.0171)	-0.2994*** (0.1125)	-0.0890 (0.1012)	-0.0077*** (0.0022)	0.0010* (0.0005)
Mean distance	0.0003* (0.0002)	-0.0005** (0.0003)	-0.0007** (0.0003)	0.0001*** (0.0000)	0.0000*** (0.0000)
VOL	-0.0218* (0.0115)	0.1418* (0.0733)	0.3028*** (0.0676)	-0.0031* (0.0019)	-0.0010*** (0.0004)
DGROWTH	-0.1611*** (0.0363)	0.8794*** (0.1261)	1.2991*** (0.1846)	-0.0108** (0.0054)	-0.0045*** (0.0009)
DCS	-0.0119* (0.0072)	0.3445*** (0.0647)	0.5779*** (0.0859)	0.0031 (0.0041)	-0.0008 (0.0005)
OPP	-0.0796*** (0.0114)	0.2958*** (0.0952)	0.3580** (0.1608)	-0.0049 (0.0050)	-0.0002 (0.0009)
CS	0.0001 (0.0001)	-0.0023*** (0.0006)	-0.0044*** (0.0007)	0.0000 (0.0000)	0.0000 (0.0000)
GDP	0.0050 (0.0499)	0.5830*** (0.1003)	0.2056 (0.1459)	0.0102* (0.0052)	-0.0000 (0.0007)
Size	-0.0734 (0.0472)	-0.0304** (0.0151)	-0.0655 (0.0441)	-0.0172*** (0.0018)	-0.0004** (0.0002)
Cash	0.2295 (0.2390)	-0.5327*** (0.0985)	-0.7272 (1.0193)	0.0002 (0.0152)	0.0087** (0.0037)
LIB	-0.0009 (0.0022)	-0.0014 (0.0136)	-0.0003 (0.0231)	-0.0010 (0.0006)	0.0001 (0.0001)
Year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	130366	130366	130366	130366	130366
Banks	10031	10031	10031	10031	10031
Within R2	0.0169	0.0058	0.0039	0.0392	0.0042

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 4: Out-of-state deposits shares

Dependent variable:	Out-of-state deposits share					
	(1)	(2)	(3)	(4)	(5)	(6)
OPP	0.0187*** (0.0014)	0.0184*** (0.0011)	0.0184*** (0.0011)	-0.0063 (0.0040)		-0.0055 (0.0039)
DIS	-0.0128 (0.1415)					
OPP × DIS	0.7018* (0.3767)	0.9970** (0.3959)	0.9970** (0.3959)	0.9153*** (0.3353)	0.7473** (0.3329)	
OPP × DIS(94)						0.7509*** (0.2707)
DCS				-0.0187*** (0.0029)		-0.0183*** (0.0029)
CS				0.0002*** (0.0000)		0.0001*** (0.0000)
DGROWTH				0.0104* (0.0057)		0.0105* (0.0057)
GDP				-0.0160*** (0.0054)		-0.0162*** (0.0054)
ROA				-0.0003** (0.0001)	-0.0003** (0.0001)	-0.0003** (0.0001)
Cash				0.0009 (0.0032)	0.0027 (0.0032)	0.0007 (0.0032)
EQ				0.0447*** (0.0080)	0.0501*** (0.0081)	0.0447*** (0.0080)
Size				0.0113*** (0.0017)	0.0119*** (0.0017)	0.0113*** (0.0017)
Mean distance				0.0007*** (0.0001)	0.0007*** (0.0001)	0.0007*** (0.0001)
VOL				-0.0006 (0.0031)		-0.0005 (0.0030)
LIB				0.0016*** (0.0006)		0.0016*** (0.0006)
Constant	-0.0012*** (0.0004)					
Year FE	No	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	No	No	No	Yes	No
Observations	156139	156139	156139	156139	156139	156139
Banks	11926	11926	11926	11926	11926	11926
Within R2	0.0093	0.0187	0.0187	0.3454	0.3458	0.3451
OPP at	MFX of DIS					
0	-0.0128 (0.1415)					
25th	0.1913 (0.1172)	0.2899** (0.1151)	0.2899** (0.1151)	0.2662*** (0.0975)	0.2173** (0.0968)	0.2184*** (0.0788)
50th	0.2900** (0.1390)	0.4302** (0.1708)	0.4302** (0.1708)	0.3949*** (0.1447)	0.3225** (0.1437)	0.3240*** (0.1168)
75th	0.3592** (0.1630)	0.5285** (0.2098)	0.5285** (0.2098)	0.4852*** (0.1777)	0.3961** (0.1765)	0.3980*** (0.1435)
1	0.6890** (0.3147)	0.9970** (0.3959)	0.9970** (0.3959)	0.9153*** (0.3353)	0.7473** (0.3329)	0.7509*** (0.2707)

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. The bottom of this table shows marginal effects for *DIS* on *EXP* at zero and full expansion opportunities as well as for the 25th, 50th, 75th percentile.

Table 5: Robustness

Dependent variable: Specification	Out-of-state deposits				
	Log dependent variable (1)	Volatility of DIS (2)	Before 2007 (3)	Twoway clustering (4)	Commercial banks (5)
OPP at	MFX of DIS				
25th	16.1687*** (5.0843)	0.0351** (0.0149)	0.2711* (0.1400)	0.2662*** (0.0932)	0.3014** (0.1193)
50th	23.9903*** (7.5386)	0.0521** (0.0221)	0.4023* (0.2077)	0.3949*** (0.1382)	0.4472** (0.1772)
75th	29.4709*** (9.2613)	0.0640** (0.0271)	0.4942* (0.2552)	0.4852*** (0.1697)	0.5493** (0.2176)
1	55.5979*** (17.4744)	0.1208** (0.0511)	0.9322* (0.4814)	0.9153*** (0.3203)	1.0363** (0.4106)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	156139	156139	119279	156139	130935
Banks	11926	11926	11926	19	10085
Within R2	0.1600	0.3452	0.3436	0.3454	0.3257

Notes: This table shows marginal effects for *DIS* at full expansion opportunities as well as for the 25th, 50th, 75th percentile for different dependent variables or samples as indicated by the column headers. 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: Interactions

Dependent variable: Interaction:	Out-of-state deposits share			
	Size	MBHC	MSBHC	VOL
OPP and interaction at	MFX of DIS			
25th / 0	0.0016 (0.0240)	0.1828** (0.0748)	0.1691** (0.0729)	0.3827*** (0.1138)
25th / 1	0.2893*** (0.1050)	0.7293 (0.5100)	1.7958*** (0.4786)	0.2980*** (0.1146)
50th / 0	0.0024 (0.0356)	0.2712** (0.1110)	0.2509** (0.1081)	0.5679*** (0.1688)
50th / 1	0.4293*** (0.1559)	1.0821 (0.7561)	2.6646*** (0.7123)	0.4422*** (0.1701)
75th / 0	0.0030 (0.0437)	0.3332** (0.1364)	0.3083** (0.1329)	0.6976*** (0.2074)
75th / 1	0.5274*** (0.1914)	1.3293 (0.9297)	3.2733*** (0.8723)	0.5432*** (0.2090)
1 / 0	0.0056 (0.0824)	0.6286** (0.2573)	0.5815** (0.2507)	1.3161*** (0.3913)
1 / 1	0.9949*** (0.3616)	2.5079 (1.7533)	6.1752*** (1.6458)	1.0248*** (0.3942)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	156139	156139	156139	156139
Banks	11926	11926	11926	11926
Within R2	0.3454	0.3479	0.3548	0.3459

Notes: This table shows marginal effects for *DIS* on *EXP* at full expansion opportunities as well as for the 25th, 50th, 75th percentile for two groups of banks as indicated by the column headers. 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: Damages and volatility

Dependent variable:	DISY (1)	SD(DISY) (2)
OPP at	MFX of DIS	
25th	-0.0390** (0.0173)	-0.2543** (0.1150)
50th	-0.0578** (0.0257)	-0.3773** (0.1706)
75th	-0.0710** (0.0316)	-0.4635** (0.2095)
1	-0.1340** (0.0596)	-0.8745** (0.3953)
Controls	Yes	Yes
Year FE	Yes	Yes
Bank FE	Yes	Yes
Observations	156139	156139
Banks	11926	11926
Within R2	0.0587	0.0609

Notes: This table shows marginal effects for *DIS* on *DISY* and *SD(DISY)* at full expansion opportunities as well as for the 25th, 50th, 75th percentile. 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: Correlations

Dependent variable:	Correlations					
	(1)	(2)	(3)	(4)	(5)	(6)
OPP at	MFX of DIS					
0	0.1774 (0.1414)					
25th	0.3501** (0.1697)	0.3358** (0.1683)	0.3358** (0.1683)	0.3857** (0.1679)	0.3650** (0.1743)	0.1418** (0.0614)
50th	0.4336* (0.2233)	0.4983** (0.2497)	0.4983** (0.2497)	0.5723** (0.2491)	0.5416** (0.2587)	0.2104** (0.0911)
75th	0.4921* (0.2667)	0.6121** (0.3067)	0.6121** (0.3067)	0.7031** (0.3060)	0.6653** (0.3177)	0.2585** (0.1119)
1	0.7710 (0.4967)	1.1548** (0.5787)	1.1548** (0.5787)	1.3263** (0.5773)	1.2552** (0.5994)	0.4876** (0.2111)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	Yes	Yes
State \times Year FE	No	No	No	No	Yes	No
Observations	156139	156139	156139	156139	156139	156139
Banks	11926	11926	11926	11926	11926	11926
Within R2	0.0048	0.0048	0.0048	0.0089	0.0047	0.0081

Notes: This table shows marginal effects for *DIS* on *CORR* at zero and full expansion opportunities as well as for the 25th, 50th, 75th percentile for Equation (4). 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: Interactions

Dependent variable: Interaction:	Size	Correlations		
OPP and interaction at		MBHC	MSBHC	VOL
		MFX of DIS		
25th / 0	0.0165 (0.0187)	0.2546** (0.1265)	0.2269** (0.1143)	0.1489 (0.1108)
25th / 1	0.4180** (0.1821)	1.0772 (0.8140)	2.9491* (1.5198)	0.4938** (0.2065)
50th / 0	0.0245 (0.0278)	0.3778** (0.1877)	0.3367** (0.1696)	0.2209 (0.1644)
50th / 1	0.6201** (0.2703)	1.5984 (1.2077)	4.3757* (2.2549)	0.7327** (0.3065)
75th / 0	0.0301 (0.0341)	0.4641** (0.2306)	0.4136** (0.2083)	0.2714 (0.2019)
75th / 1	0.7618** (0.3320)	1.9635 (1.4836)	5.3754* (2.7689)	0.9001** (0.3765)
1 / 0	0.0567 (0.0644)	0.8756** (0.4351)	0.7803** (0.3930)	0.5120 (0.3809)
1 / 1	1.4372** (0.6263)	3.7042 (2.7989)	10.1409* (5.2343)	1.6980** (0.7109)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	156139	156139	156139	156139
Banks	11926	11926	11926	11926
Within R2	0.0090	0.0099	0.0138	0.0094

Notes: This table shows marginal effects for *DIS* on *CORR* at full expansion opportunities as well as for the 25th, 50th, 75th percentile for two groups of banks as indicated by the column headers. 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.