Natural Disasters, Local Bank Market Share, and Economic Recovery

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Abstract

Interstate bank deregulation in the US during the 1980s and 1990s led to larger, nationally diversified banks, and a decline in the number of community banks. Economic theory suggests that community (or "local") banks may have a greater incentive, but a lower capacity, to lend to a region following a destructive event such as a natural disaster. We test whether regions with more local banking institutions at the time of a natural disaster have greater post-disaster lending, and as a consequence, more rapid regional redevelopment characterized by higher employment and wages and greater population growth. Overall, there is a small reduction in lending in the years immediately following a large disaster. We estimate that there are fewer new home loans in counties with a lower share of local banking at the time of the disaster. We do not find any post-disaster difference in county-level economic outcomes, based on the intensity of local banking at the time of a disaster. One possible explanation as to why an increase in credit to the disaster region doesn't lead to improved economic development post-disaster is that we are, so far, unable to examine differences in business lending in our empirical setup.

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1 Introduction

Faster economic growth (e.g. Schumpeter [1969]) and improved economic stability (e.g. Demyanyk et al. [2007]) were prominent arguments for the interstate deregulation in the 1980s and 1990s that encouraged larger, nationally diversified US banks. Geographically diversified banks are not as vulnerable to a local shock to their own capital. Interstate (or "non-local") banks may also have a greater capacity to lend to a region that suffers an economic shock. Non-local banks can shift capital from other geographic regions in which they operate, and thereby increase credit to residents in the disaster region suffering an economic shock (e.g. Cortes and Strahan [2017]).

Community (or "local") banks are defined by the Federal Deposit Insurance Corporation (FDIC) as banks that focus on local lending and which have relatively few total assets (FDIC [2012]). Economic theory suggests that, while community banks may have less capital to lend to the region following a destructive event such as a natural disaster, these banks may also have a greater incentive to lend (e.g. Morgan et al. [2004]). A reduction in borrower capital following a disaster makes lending to the disaster region more risky. Non-local banks may shift lending to other regions in which the bank operates where there is less-costly monitoring or higher expected returns.

This paper asks two main research questions. First, do locations with a higher share of local banking at a time of a natural disaster have greater aggregate lending post-disaster? Differences in the cost of information acquisition, business incentives, and the financial stability between local and non-local lenders could affect post-disaster lending decisions (e.g. Berger and Udell [2002]; Gallagher and Hartley [2017]). Second, do differences in post-disaster lending that are attributable to the composition of local banking at the time of the disaster affect regional economic recovery and redevelopment? Aggregate credit post-disaster could determine longer-run regional economic development if initial post-disaster reinvestment affects the path dependence of future economic growth (e.g. Kline and Moretti [2014]), there are economies of agglomeration (e.g. Bleakley and Lin [2012]; Glaeser [2011]), or there are social externalities such that residents are more likely to stay and rebuild in the disaster-impacted region if their neighbors also stay (e.g. Fu and Gregory [2019]; Paxson and Rouse [2008]). Hsiang and Jina [2014] summarize four potential post-disaster development outcomes that range from "no recovery" to "creative destruction", depending on the speed and level of economic development.

We focus on natural disasters because these events are random, costly, and widespread shocks to local US economies. Overall, the US experienced $400 billion in damage from the 14 most costly natural disasters in 2019 (NOAA [2020]). The Federal Emergency Management Agency (FEMA) declared 101 state-level disasters the same year (FEMA [2019]). Moreover, the economic cost of natural disasters in the US is likely to increase in the coming decades due to the geography of development, and an increase in the frequency and size of natural disasters from climate change (e.g. Bouwer et al. [2007]; Kunreuther et al. [2013]). Thus, a better understanding of how local economies evolve following natural disasters is of independent interest (e.g. Roth Tran and Wilson [2021]).

We build a new national database in order to investigate our research questions. The database is a yearly county-level panel from 1980-2014 and includes all (more than one thousand state-level Presidential Disaster Declarations, where each declaration designates the counties impacted by a large natural disaster. We use federal disaster assistance information as a proxy for disaster cost, which allows us to estimate how lending and disaster recovery respond based on the severity of the natural disaster.[1] The database includes information on nearly all new home (1990-2014) and business (1997-2014) loans. Our main economic outcomes are changes in average county-level employment, wages, population, and property values.[2]

We estimate event study and difference-in-differences models that allow for the time-varying impact of a natural disaster on the regional economy, based on the share of local banking in the year before the disaster. We use FDIC bank deposits information to construct a measure of local banking for each county during each year based on the location of bank deposits. The county local banking index ranges from 0 to 1. A higher local banking index implies that a larger share of banking in the county is done by local lenders. The main empirical challenge is that the development of local banking institutions is endogenous to local economic conditions. We address the endogeneity of the local bank market share through the use of an instrumental variables model that leverages the timing of interstate and intrastate banking deregulation. Bank deregulation occurred state-by-state from 1982-1994. The timing of state-level deregulation did not depend on state economic conditions

[1] Another approach is to model the severity of the storm using meteorological information, rather than actual disaster cost (e.g. Deryugina [2017]). However, the meteorological information that allows for this type of modeling is only available for a small subset of natural disasters such as large hurricanes and tornadoes.

[2] We are still compiling the property sales data and do not analyze these data in the current draft.

or state banking profitability (e.g. Jayaratne and Strahan [1996]; Levine et al. [2020]) and strongly predicts the future local banking index.

Overall, there is a small reduction in lending in the years immediately following a large disaster. We estimate that the total amount of new home loans is less in counties with a lower share of local banking at the time of the disaster. We do not find any post-disaster difference in county-level economic outcomes based on the intensity of local banking at the time of a disaster. One possible explanation as to why an increase in credit to the disaster region doesn't lead to improved economic development post-disaster is that we are, so far, unable to examine differences in business lending in our model. There is also some evidence that differential trends in home lending prior to a disaster between locations with more and less local banking may contribute to the observed post-disaster lending difference.

This paper adds to the literature that examines locally focused private lending institutions and the level of post-disaster credit to a region (e.g. Chavaz [2016]; Collier and Babich [2019]; Cortes and Strahan [2017]; Gallagher and Hartley [2017]). Gallagher and Hartley [2017] show that whether a lender is local appears to affect post-disaster lending in New Orleans following Hurricane Katrina. Non-local lenders dramatically decreased lending to New Orleans following Hurricane Katrina, while local lenders continued to lend at pre-Katrina levels. Cortes and Strahan [2017] examine a ten year sample of US natural disasters and find that financially integrated (non-local) banks increase lending post-disaster in disaster regions. Neither study accounts for the endogenous development of banking institutions nor examines differences in *total* lending to a region.

This paper also contributes to the literature that examines how natural disasters impact national (e.g. Cavallo et al. [2013]; Hsiang and Jina [2014]) and regional (e.g. Boustan et al. [2020]; Tran and Wilson [2021]; Strobl [2011]) economies. One question that has largely been ignored in this literature is the role that local banking institutions have on post-disaster recovery.[3] We are not aware of any existing research that links the composition of local and non-local banking in a region at the time of a natural disaster with future economic growth.

Our results highlight that community banks appear to have an under-recognized role in providing credit following a natural disaster. Overall, residents in rural counties are more dependent on

[3]A notable exception is Collier and Babich [2019], who examine the amount of credit supplied by local lenders following a natural disaster in a cross-country sample of developing countries.

lending from community banks. Community banks are about three times more likely than non-local banks to have a banking office outside a metro area (FDIC [2012]). At the same time, residents in rural counties have lower wages and face higher unemployment than those living in urban counties (Moretti [2012]). Public policies that support the role of community banks may be particularly helpful to residents in rural areas who are more vulnerable to an economic shock.

2 Background and Data

2.1 Theoretical Framework

Asymmetric information and moral hazard have long been known to limit credit availability (e.g. Rothschild and Stiglitz [1976]; Spence [1973]). In this section, we outline a theoretical framework based on several previous contributions (e.g. Holmstrom and Tirole [1997]; Morgan et al. [2004]; Townsend [1979]).

In the Townsend [1979] costly state verification model, lenders must pay a fixed cost to observe a borrower's return on a loan. The model predicts that some borrowers with a positive expected return on their investment will not receive a loan, and that laws which restrict the activity of lenders (e.g. interstate banking restrictions) will reduce overall credit to a region. The model assumes that banks are homogeneous. A large literature in finance and economics has subsequently argued that community banks have an informational advantage that can lower the cost to both screen and monitor borrowers (e.g. Berger and Udell [2002]; Hein et al. [2005]; Nguyen [2019]).

Holmstrom and Tirole [1997] model how capital-constrained financial intermediaries (banks) allocate credit when there is potential borrower moral hazard. Costly monitoring by banks and higher levels of borrower collateral can prevent moral hazard. The Holmstrom and Tirole [1997] model predicts that a natural disaster that reduces either borrower collateral or bank capital will lead to less credit in the disaster region. Morgan et al. [2004] expand the Holmstrom and Tirole [1997] model to include multiple bank lending locations. The innovation is to capture US banking deregulation (an "interstate banking" system) that leads banks to decide both how much to lend, as in Holmstrom and Tirole [1997], and where to lend.

The Morgan et al. [2004] model is the basis for our theoretical predictions. We extend the intuition of the model in two ways. First, we conjecture that in an interstate banking system, that bank lending to homeowners can be modeled similarly to bank lending to entrepreneurs. Second, Morgan et al. [2004] focus on a binary definition. The banking system is either interstate or not interstate. We hypothesize that the *degree* a region is exposed to interstate banking can determine whether, on net, credit to a disaster region increases or decreases post-disaster. There are three main predictions:

1. **Capacity.** Local banks have *less capacity* to lend to a disaster impacted region. Local banks are less geographically diversified and less able to import capital from another geographic region. The lower capacity to lend in regions with a higher share of local banking will, *all else equal*, <u>decrease</u> post-disaster lending as compared to regions with a lower share of local banking.

2. **Incentive.** Local banks have a *greater incentive* to lend to a disaster impacted region. A collateral shock to borrowers will make lending to the disaster impacted region more costly due to higher moral hazard when collateral has been destroyed. Non-local banks will shift lending to other regions that now have a higher expected return. Local banks have fewer opportunities to lend outside the disaster impacted region, and have an interest in promoting the economic recovery of their banking area. The greater incentive to lend in regions with a higher share of local banking will, *all else equal*, <u>increase</u> post-disaster lending as compared to regions with a lower share of local banking.

3. **Information.** Local banks may be able to better assess risk and to monitor borrowers at a lower cost. Monitoring rebuilding may be especially important after a natural disaster. The informational advantage in regions with a higher share of local banking will, *all else equal*, <u>increase</u> post-disaster lending as compared to regions with a lower share of local banking.

The capacity prediction goes in the opposite direction as the incentive and information predictions. How the level of local banking affects post-disaster lending is not clear a priori.

2.2 Bank Deregulation as a Source of Exogenous Local Banking

Local banking institutions are not randomly assigned geographically. Local bank development is endogenous to the size and wealth of the local population, among other factors. At the same time, locations with a larger or wealthier population may be more able to cope with the negative economic shock of a natural disaster (e.g. Lackner [2019]; Roth Tran and Wilson [2021]). Econometric models that seek to estimate the causal effect of stronger local banking institutions, such as the local bank market share, on post-disaster recovery of the local economy, are likely to be biased unless the model accounts for the geographic endogeneity of the banking institutions. We address the endogeneity of local bank market share through the use of an instrumental variable model that leverages the timing of interstate and intrastate banking deregulation. Our implementation closely follows Morgan et al. [2004] and utilizes the deregulation years from Table 1 in their paper.

2.2.1 A Brief History of the Geography of Bank Deregulation

There are four ways for a bank to geographically expand: interstate banking, interstate branching, intrastate banking, and intrastate branching. Branching involves establishing an affiliated office that is not separately chartered or capitalized. Geographic expansion through banking involves acquiring a new charter.

Historically, the US banking system was characterized by fragmented state-level banking markets (e.g. Johnson and Rice [2007]). Two-thirds of the US states restricted within state bank branching as of 1979. Prior to 1982, no bank was able to operate in multiple states (per the 1956 Holding Company Act). Maine was the first state to pass interstate deregulation in 1978. The Maine law was a reciprocity agreement whereby banks chartered in another state could operate in Maine, provided Maine banks received the same accommodations. Modern interstate banking began when Alaska and New York also passed interstate reciprocity agreements in 1982. Interstate or intrastate deregulation was passed by at least one state in each year 1980-1994 (see Table 1). The Reigle-Neal Interstate Banking and Branching Efficiency Act of 1994 established interstate banking as a bank right (e.g. Mulloy and Lasker [1995]). States could no longer prohibit out-of-state banks from entering.[4]

A key condition in establishing deregulation as a valid source of exogenous variation for local banking is that the timing of deregulation is uncorrelated with state-level banking supply and demand. Numerous studies conclude that the timing of state-level deregulation does not correlate

[4]States still retained scope to limit the expansion of out-of-state banks by, for example, instituting a more stringent statewide deposit concentration limitation for interstate banks than that set (30%) by the 1994 law (e.g. Rice and Strahan [2010]).

with state economic conditions or state banking profitability (e.g. Jayaratne and Strahan [1996]; Levine et al. [2020]; Morgan et al. [2004]).

2.2.2 Local Banking Index using Bank Deposits

We use FDIC bank deposit information to define a measure of local banking activity in a county each year, similar to Cortes and Strahan [2017]. The bank deposit information includes the total deposits for every bank and holding company operating in each county every year beginning in 1981. Unique FDIC ids track lenders across counties and years. We define a lender as each unique holding company, or as the company itself if it is not part of a holding company.

We assign each county a local banking index between zero and one each year using the following equation:

$$LocalBanking_{ct} = \sum_{l=1}^{L} (LenderLocalness_{lct}) * (LenderShare_{lct}) \tag{1}$$

LenderLocalness is defined as the total deposits by lender l in county c in year t, divided by the total deposits held by that lender in year t. *LenderShare* is the total deposits by lender l in county c for year t, divided by the total deposits held by all lenders in county c in year t. The county local banking index is a weighted sum of each lender's localness measure, with weights based on the share of each lender's total deposits in the county. A higher local banking index implies that a larger share of banking in the county is done by local lenders.

2.2.3 Deregulation and Local Banking

Figure 1 shows how bank deregulation can be used to isolate plausibly exogenous variation in the intensity of local banking. Panel A plots the mean county bank index for Illinois (circles) and Arkansas (diamonds) from 1982-2000. The dashed vertical lines mark the year that each state passed *interstate* deregulation. The solid vertical lines mark the year when each state passed *intrastate* deregulation. These two states are selected because the mean local bank indices were nearly identical in 1982. The index declines at the same rate in both states for the first three years. Illinois passed interstate deregulation in 1986, at which point the indices began to diverge. The mean local bank index was lower in Illinois in 1987 by about 5 percentage points. Illinois then passed intrastate deregulation in 1988. The gap between the Illinois and Arkansas indices increased to about 10 percentage points in 1989. The gap only began to narrow after Arkansas passed interstate deregulation in 1989. Arkansas passed intrastate deregulation in 1994. Beginning in 1994, the index was lower in Arkansas.

Figure 1 panel B shows the mean county local bank index for the eight states where interstate deregulation occurred three or more years before intrastate deregulation. Five of the states (Colorado, Indiana, Kentucky, Minnesota, Missouri) exhibit a trend break at or just after the year of interstate deregulation (shaded region) that reduces the share of local banking.

2.3 Data Sources

The FDIC bank deposits data and the bank deregulation information are described in Section 2.2. The remaining data sources are listed below.

2.3.1 Natural Disaster Incidence and Cost

The natural disaster data include all Presidential Disaster Declarations (PDDs) from 1981-2014. Disaster declarations are at the county-level. The disaster cost information is from FEMA's Public Assistance program. Public Assistance is available to local governments and non-profit organizations to repair infrastructure and to aid in the reconstruction of public buildings. Public Assistance is a consistent measure of disaster cost over time that avoids the missing data concerns associated with the commonly used SHELDUS weather damage database (SHELDUS [2020]). Missing data in SHELDUS are not random (Gallagher [2021]).

A drawback of the Public Assistance cost information is that the data are only available at the disaster level (aggregated across counties) for most PDDs prior to 1990. We use county-level Public Assistance data when we restrict our analysis to PDDs occurring from 1990-2014. These data are compiled from a Freedom of Information Act Request and from FEMA's website (beginning in 2004). The amount of Public Assistance among PDD counties is log normally distributed, and the median PDD county incurs approximately \$500,000 in damage (see Figure 1). Note that hereafter we use Public Assistance data when we refer to the "cost" of a natural disaster. Flood cost and all other dollar-denominated variables are adjusted using the Consumer Price Index to real 2014\$.

2.3.2 Bank Loans and Economic Information

There are two sources for bank loans. Home loan information is from the Home Mortgage Disclosure Act (HMDA). The loan data include the dollar amount of the loan and the type of loan (e.g. mortgage or line of credit) for all new loan originations in each county and year. The HDMA data are available beginning in 1990. Business loan information is from the Federal Financial Institutions Examination Council (FFIEC) and available beginning in 1997. Both databases contain unique lender ids that allow us to track loans made by the same lender in different counties and years. Our main analysis uses home loans, as the length of the available panel limits the use of business loans. However, we show that county-level home lending is highly correlated with business lending (see Figure 2).

County-level economic information is from a variety of sources (1980-2014). We use County Business Patterns employment data, wage information from the US Bureau of Economic Analysis, and population data from the National Bureau of Economic Research.[5]

3 Statistical Model

3.1 Estimation

Equation 2 is an event study model that allows for estimation of the time-varying impact of a natural disaster on the regional economy based on the share of local banking in the year before the disaster. The model estimates a heterogeneous treatment effect using a continuous pre-treatment characteristic (e.g. Card [1992]).

$$\begin{aligned} y_{ct} = \sum_{\tau=-a}^{b} \alpha_\tau 1[LargeDisaster_{c\tau}] + \sum_{\tau=-a}^{b} \delta_\tau 1[LargeDisaster_{c\tau}] * LocalBanking_{c\tau=-1} + \\ \sum_{\tau=-a}^{b} \beta_\tau 1[OtherDisaster_{c\tau}] + X_{ct}\beta + \lambda_c + \eta_{dt} + \epsilon_{ct} \quad (2) \end{aligned}$$

y_{ct} is a local economic outcome, such as new loans (credit) or the employment rate, in county c in year t. Equation 2 allows for disasters to have a different economic impact based on their

[5] We are also in the process of integrating property value information from CoreLogic.

magnitude, as measured by their cost. Our baseline models define a *LargeDisaster* as one that exceeds the 75th cost percentile. The *OtherDisaster* variable captures the effect of a PDD that is below the cost threshold. α_τ and β_τ are the event time coefficients for a large and other disaster, respectively, where $\tau = t - E_i$ is event time, E_i is the year of a disaster, a and b are the number of leads and lags included, and 1[ ] is an indicator function. The number of lead and lag effects depends on the sample. We defer the discussion of our samples to the next subsection.

δ_τ are the coefficients of interest and measure how the impact of a large disaster varies post-disaster based on a region's banking institutions at the time of the large disaster. $LocalBanking_{ct}$ is constructed using Equation 1. The value of $LocalBanking_{ct}$ in the year before a large disaster is interacted with each (post) large disaster event time indicator. County fixed effects (λ_c) account for factors specific to a county that do not change during our panel (e.g. geographic location). Note that the $LocalBanking_{ct}$ in the year before a disaster is not time varying and is subsumed by the county fixed effects. Census Division by year fixed effects (η_{dt}) flexibly control for common calendar time factors (e.g. economic conditions, population trends) that may differ by region of the country.[6]

X_{ct} contains two control variables: the amount of Small Business Administration (SBA) disaster loans, and the fraction of the population that is covered by flood insurance. SBA disaster loans are available to homeowners and businesses following a PDD. Approximately, two-thirds of PDDs involve flooding and home and business owners must purchase a separate insurance policy (beyond the standard home or business insurance) to cover flood-related costs. The level of SBA disaster loans and flood insurance coverage could affect the demand for new bank credit following a disaster. However, both variables are potentially endogenous and are not included in our baseline specification. We cluster the standard errors at the state level to allow for geographic correlation in the occurrence of a natural disaster. Finally, we note that the event time indicators are binned in some specifications so as to summarize the impact for the following time periods: pre-disaster, year of disaster, 1-5 years post-disaster (short run), and 6-10 years post-disaster (medium run).

The recent methodological literature on event studies has shown several potential limitations when the model is estimated using ordinary least squares (OLS) (e.g. Borusyak et al. [2021];

[6] There are nine Census Divisions. We do not use state-by-year fixed effects since the deregulation variation that we use for exogenous variation of the county local banking share is at the state-level.

Sun and Abraham [2021]). As a robustness model, we follow Borusyak et al. [2021] and use an imputation-based estimation approach. One drawback is that this imputation approach does not allow for a continuous treatment. We run the imputation-based model on a version of Equation 2 that excludes the interacted local banking variable. Thus, we are not able to use this model to test our main hypotheses, but can use the imputation model as a (partial) test for whether the timing of large disasters satisfy the parallel trends identifying assumption.

We instrument for bank localness using Equation 3.

$$LocalBanking_{ct} = \gamma_1 1(Interstate)_{ct} + \gamma_2 1(Intrastate)_{ct} + \gamma_3 InterstateLag_{ct} + \gamma_4 InterstateLag_{ct} \\ + \sum_{\tau=-a}^{b} \alpha_\tau 1[LargeDisaster_{c\tau}] + \sum_{\tau=-a}^{b} \beta_\tau 1[OtherDisaster_{c\tau}] + X_{ct}\beta + \sigma_c + \phi_{dt} + \nu_{ct} \quad (3)$$

Interstate and *Intrastate* are indicator variables equal to one beginning in the year that a state first passes interstate and intrastate deregulation, respectively. *InterstateLag* and *IntrastateLag* equal zero before the year of deregulation, and then increment by one each year beginning in the year of deregulation. These lag variables capture the time since the start of deregulation. The effect of deregulation on the intensity of local banking institutions likely depends on the time since the change in the law. The exogenous deregulation variables are omitted from Equation 2. The other variables in Equation 3 are the disaster indicators, and county (σ_c) and Census Division by year (ϕ_{dt}) fixed effects. We also include the SBA disaster loan and flood insurance coverage variables (X_{ct}) in some specifications. We cluster the standard errors at the state level.

Callaway et al. [2021] show that the standard parallel trends assumption, that the potential outcomes for treated and untreated units evolve the same in the absence of treatment, is typically not sufficient for continuous treatment event study models. A stronger parallel trends assumption is required. In our setting, we must assume that the average potential outcomes for disaster counties are the same for counties with *each* level of the *predicted* local banking index in the year before the disaster. In other words, there is no county-level endogenous selection of the *predicted* local banking index.

3.2 Samples

Our main sample includes information from 1990-2010. The objective is to best leverage the power of our deregulation instrument, while still evaluating the long-run post-disaster impact on regional development. The samples are balanced in event time. Treated counties are defined as those with only one large disaster which occurs between 1993-2000. Each treated county has 14 observations (3 pre-treatment, year of large disaster, 10 post-treatment). We use county-level FEMA cost information to define a large disaster and a 75th percentile cost threshold. We drop counties that are hit by more than one large disaster between 1993-2000, but we allow counties that are hit by a large disaster 1993-2000 to be hit by another large disaster in subsequent years (2001-2010). The logic is that treatment status is permanent. The 1980s and 1990s represent the period of bank deregulation when there are large changes to county-level banking markets. We control for the timing of future large disasters in the same way as we do for smaller disasters.[7] We also include all counties that are never hit by a large disaster (1990-2010).

The advantage of this sample is that home loan and disaster cost data are available at the county-level. County-level cost information provides a precise measure of a disaster's destruction in each county. The loan information allows us to estimate the disaster's impact on bank lending and economic recovery from the same sample. However, there are also limitations. The sample excludes economic and banking information from the 1980s, a key period in bank deregulation, and estimates an event study model with just three pre-treatment observations.[8]

4 Results

4.1 Predicted Bank Index

Table 2 shows results from using Equation 3 to predict the county local bank index for two panels: the entire sample period (1981-2014) and the 1993-2000 event time panel (main sample). The coefficient estimates for the deregulation indicator variables are negative in both specifications and

[7] Approximately, 7% of US counties have more than one large disaster during this time period. These counties are dropped from the analysis. An event study model estimated using OLS does allow for the same county to be hit by a disaster multiple times (e.g. Gallagher [2014]). However, the Borusyak et al. [2021] imputation-based approach requires that treatment for each county occurs only once.

[8] We plan to evaluate robustness of our sample to these limitations by estimating alternative samples that vary the starting date and length of the panel, among other factors.

generally statistically different from zero at 5% significance level. In our main sample, the county local bank index is 7 percentage points lower in the years following intrastate deregulation and 11 percentage points lower after interstate deregulation. Modeling the time since deregulation (the lagged variables) is more important for intrastate deregulation, which tended to occur earlier. The F-statistic that the deregulation variables are jointly different from zero is 56.4 in the full panel and 11.2 in the main sample.

4.2 Overall Impact of a Large Disaster

We estimate the overall impact of a large natural disaster on the provision of credit (home loans) to residents of the disaster county, and on three economic outcomes using the imputation-based event study model (Borusyak et al. [2021]) described in the previous section. Figure 4 shows the estimated coefficients for our main sample. The shaded regions represent the 95% confidence interval. The squares to the left of the vertical line indicate the period before a large disaster. The estimated pre-period coefficients are relative to three years before a disaster. The circles to the right of the vertical line represent the effect of the disaster and are relative to the year before a disaster (event year -1). The box at the top of each figure displays the difference-in-differences (DiD) coefficient estimate and standard error using the imputation-based model. The DiD coefficient summarizes the change in the dependent variable across the entire post-disaster period.

Overall, there is a statistically insignificant 6% reduction in new home loans during the ten years following a large disaster.[9] There is a positive effect on both employment and wage. The patterns are similar. Both outcomes peak five years after a disaster (approximately a 2% increase in employment rate and 1.5% increase in wages), before decreasing to a statistically insignificant impact by the end of the time period. There is no overall effect on population. There is no evidence of a pre-trend in any of the panels.

[9] There is an approximately 10% reduction in new home loans that is statistically significant at the 1% level if we run the same event study model with year fixed effects, rather than Census Division-by-year fixed effects.

4.3 Disaster Impact Based on Differences in Local Banking Institutions

4.3.1 New Lending

Figure 5 plots the raw data and previews our main results. The figure plots the difference in the natural log of total new home loan dollars before and after a large natural disaster (y-axis), by the predicted local bank index in the year prior to the disaster (x-axis) for our main sample. There is a positive relationship between the change in the total dollar value of new home loans and the predicted bank index. Banks operating in counties with a higher predicted bank index just prior to a large disaster increase their overall lending in the year following the disaster.

Table 3 shows our model estimates for the impact of a large disaster based on the level of local banking at the time of the disaster. We estimate the model in OLS using Equation 2 and the predicted local banking index. The post-disaster event study indicators are binned, so as to estimate the effect 1-5 years (short run) and 6-10 years (medium run) following a disaster. The binned pre-disaster indicators (2-3 years pre-disaster) provides a test for whether there are differential trends, before the disaster, based on the composition of local banking at the time of the disaster.

We estimate that a larger predicted local bank index increases the amount of new home loans post-disaster. The disaster year, short run, and medium-run interaction variables are all positive and statistically different from zero at the 1% level. In order to interpret the economic significance of these findings, we need to evaluate each interaction coefficient at a particular level of the local banking index and sum this product with the coefficients for the non-interacted disaster indicators. Figure 6 displays the economic impact for counties at the 10th, 50th, and 90th local bank index percentiles. The results for the year of a disaster are plotted in the leftmost panel. A county at the 50th percentile has approximately a 6% reduction in new home loans. This is consistent with the overall estimate from Figure 4, panel A. The estimated reduction in new home loans is larger for counties with a smaller share of local banking (approximately -15% at the 10th percentile), while there is an estimated increase in lending for counties with a larger share of local banking (approximately 15% at the 90th percentile). The estimated impact is persistent. The short-run and medium-run estimates imply similar, positive-sloped new home loan gradients.

An important caveat to our home loan findings is that there is suggestive evidence of a pre-existing trend in the level of new home loans based on the intensity of local banking in a county.

The interaction variable prior to the year of a large disaster is a similar magnitude to that of the post-disaster interaction variables, and is statistically significant from zero at the 10% level. Counties with a larger local banking index appear to be increasing home lending prior to a large disaster relative to counties with a smaller banking index.[10]

The loan results are robust to other samples and models. There is consistent evidence for an increase in post-disaster lending in counties that have a larger local bank index at the time of a disaster. However, there is also consistent evidence for some lending differences between counties with larger and smaller local bank indices in the immediate year(s) before a larger disaster.

Figure 7 shows results from a robustness model using our main sample and the imputation-based model. We separately estimate the model for counties with an above median banking index at the time of a large disaster, and for counties with a below median banking index at the time of a large disaster. We include all of the control counties in each specification. The model is run with year fixed effects, but results are similar when we include Census Division-by-year fixed effects. The left panel of Figure 7 shows a small drop in lending in locations with an above median local banking index, relative to the year before a large disaster, but this reduction is not statistically different from zero. The right panel shows a large (-18%), statistically significant reduction in new home lending that persists for the ten years following a disaster. At the same time, there is again some evidence that lending differs before a large disaster. There is a 12% reduction (statistically significant from zero at 10% level) in new lending the year before a large disaster, relative to three years before a large disaster.

4.3.2 Economic Outcomes

Table 3 columns 2-4 shows how a large disaster impacts the employment rate, total population, and average wage based on the level of local banking at the time of the disaster. None of the post-disaster interaction coefficients are statistically significant.

[10]Recall that the coefficient is negative and relative to the year before a disaster.

5 Discussion

This working paper provides new evidence on two main research questions. First, we show that counties with a higher share of local banking at a time of a large natural disaster have greater new home lending post-disaster. Second, the difference in new home lending does not translate into differences in post-disaster economic development. Counties with higher new home lending do not have (statistically significant) differences in the employment rate, average wage, or total population in the ten years following a large disaster.

We cautious in our interpretation of the results. There is suggestive evidence that new home lending may already be declining even before the disaster for counties with less local banking. In work-in-progress, we use a propensity score matching model to select control counties as a means to lesson the difference in pre-existing trends in new lending (rather than including all counties that are never hit by a large disaster 1990-2000). Preliminary results (not shown) indicate that lending is still greater post-disaster in counties with more local lending at the time of the disaster, but that this difference is smaller as compared to a model that does not explicitly account for potential differences in pre-disaster lending.

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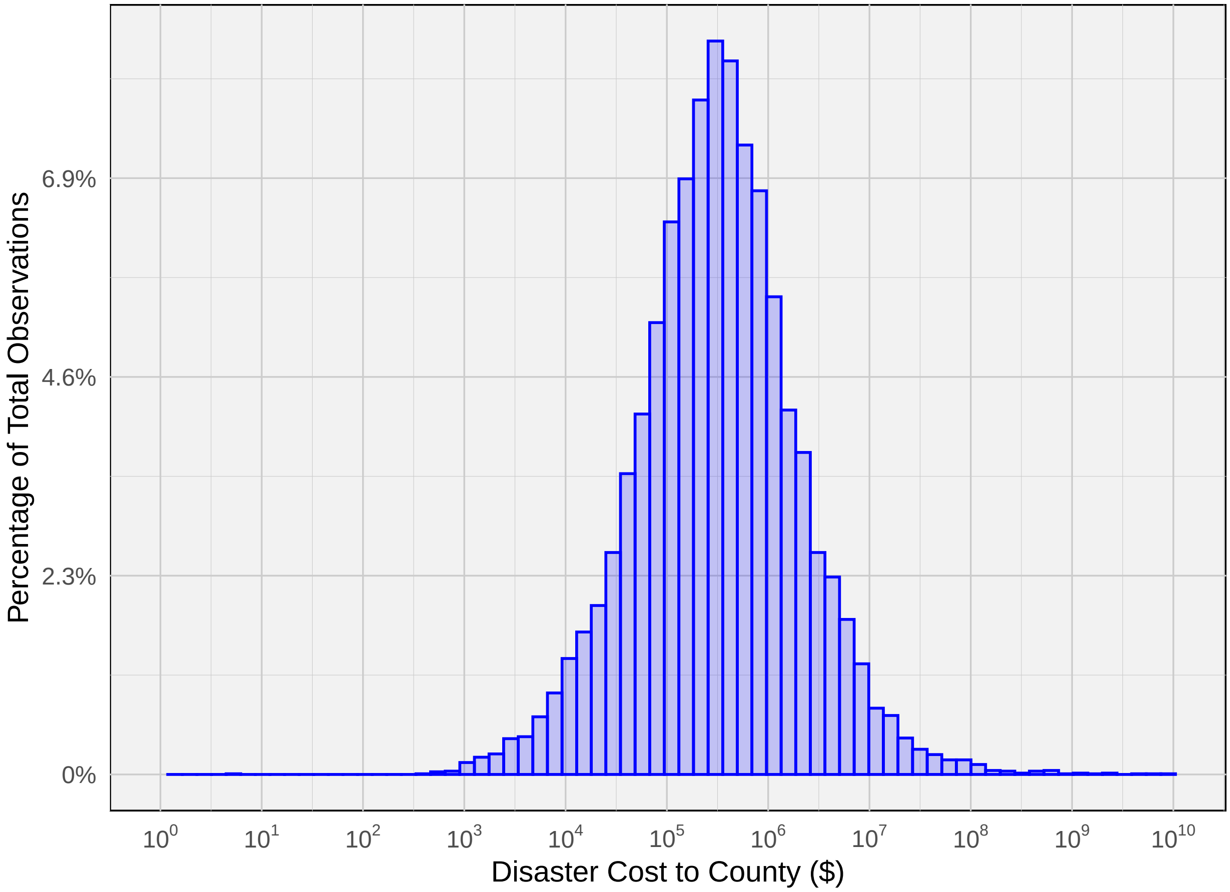
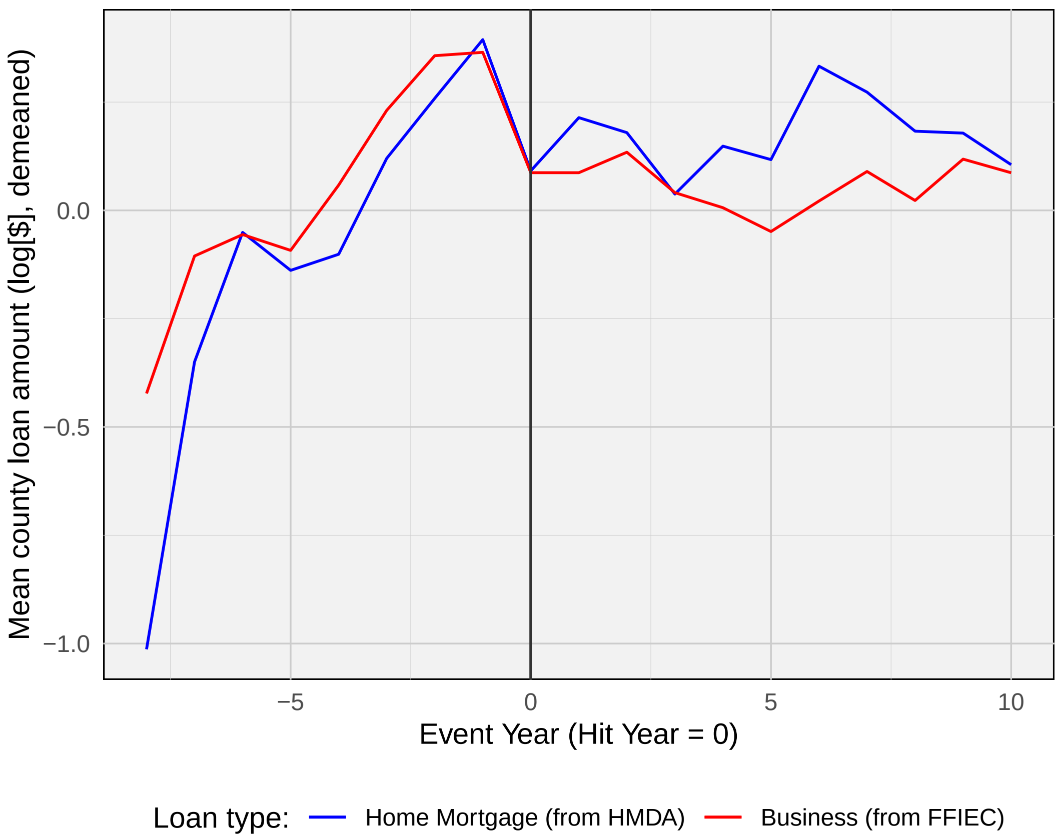
Figure 1: **Distribution of County Public Assistance**



Source: FEMA Public Assistance (1990-2014).

Figure 2: **New Home and Business Lending following a Large Natural Disaster**



The figure plots the mean level of lending (across counties, after removing county fixed effects) for counties hit by a large disaster with respect to the timing of the disaster. Sources: FEMA, HMDA, FFIEC.

Table 1: **State Banking Deregulation by Year**

Deregulation Year	States Passing Deregulation	
	Interstate	Intrastate
Pre-1980	1	16
1980	0	1
1981	0	3
1982	1	1
1983	2	1
1984	3	1
1985	9	4
1986	10	1
1987	9	5
1988	6	6
1989	2	1
1990	1	4
1991	2	2
1992	1	0
1993	1	1
1994	0	1

Source: Morgan et al. (2004).

Table 2: **Predicting the County Local Bank Index Using State-level Deregulation**

Dependent Variable: County Local Banking Index		
Sample:	1981-2014 Full Panel	1993-2000 Event Time
	(1)	(2)
Intrastate Indicator	-0.131***	-0.070**
	(0.011)	(0.031)
Interstate Indicator	-0.026	-0.111**
	(0.017)	(0.045)
Intrastate Lag	0.003***	0.009***
	(0.001)	(0.002)
Interstate Lag	0.020***	-0.020
	(0.000)	(0.027)
Disaster Indicators	X	X
Census Div by Year FE	X	X
R^2	0.751	0.812
Observations	99,106	52,838
F-Stat, Regulation	56.4	11.2

The table shows the coefficient estimates and standard errors for estimating Equation 3 on two different samples: the full panel (1981-2014), and our main panel (1993-2000 balanced event time panel). All specifications include county fixed effects and natural disaster event time indicators. Standard errors are clustered state-by-year. Significance level: *** 1%, ** 5%, * 10%. Data Sources: FDIC, Morgan et al. [2004].

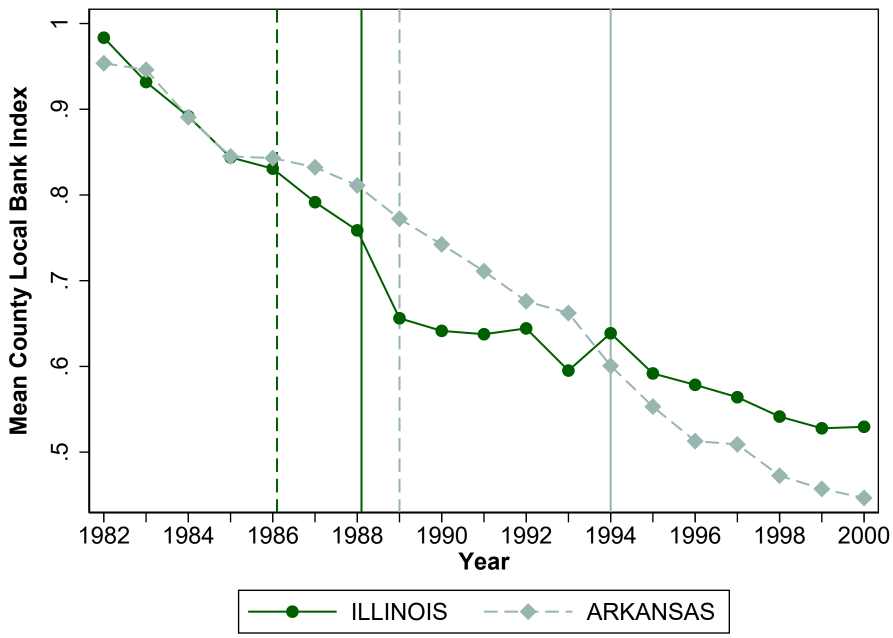
Table 3: **Disaster Impact Based on Differences in Local Banking Institutions**

Dependent Variable:	Loans	Employment	Population	Wage
	(1)	(2)	(3)	(4)
2-3 yrs pre-Disaster	0.200**	-0.001	-0.002	0.007
	(0.084)	(0.006)	(0.003)	(0.004)
Disaster Year	-0.233***	0.016***	-0.002	0.007**
	(0.054)	(0.004)	(0.002)	(0.003)
1-5 Years post-Disaster	-0.301***	0.031***	-0.001	0.017**
	(0.071)	(0.008)	(0.008)	(0.007)
6-10 Years post-Disaster	-0.307***	0.027*	0.013	-0.001
	(0.081)	(0.015)	(0.017)	(0.013)
2-3 Yrs pre-Disaster * Bank Index$_{\tau\text{-}1}$	-0.506*	-0.001	-0.005	-0.017**
	(0.277)	(0.015)	(0.005)	(0.008)
Disaster Year * Bank Index$_{\tau\text{-}1}$	0.405***	-0.017	0.004	-0.007
	(0.132)	(0.014)	(0.005)	(0.009)
1-5 Yrs post-Disaster * Bank Index$_{\tau\text{-}1}$	0.469***	-0.034	0.002	-0.013
	(0.135)	(0.021))	(0.014)	(0.014)
6-10 Yrs post-Disaster * Bank Index$_{\tau\text{-}1}$	0.507***	-0.032	-0.004	0.016
	(0.142)	(0.025)	0.027	(0.025)
County FE	X	X	X	X
Census Div by Year FE	X	X	X	X
Indicators Other Disasters	X	X	X	X
Observations	53,543	54,179	54,256	53,242
R-Squared	0.942	0.935	0.997	0.954

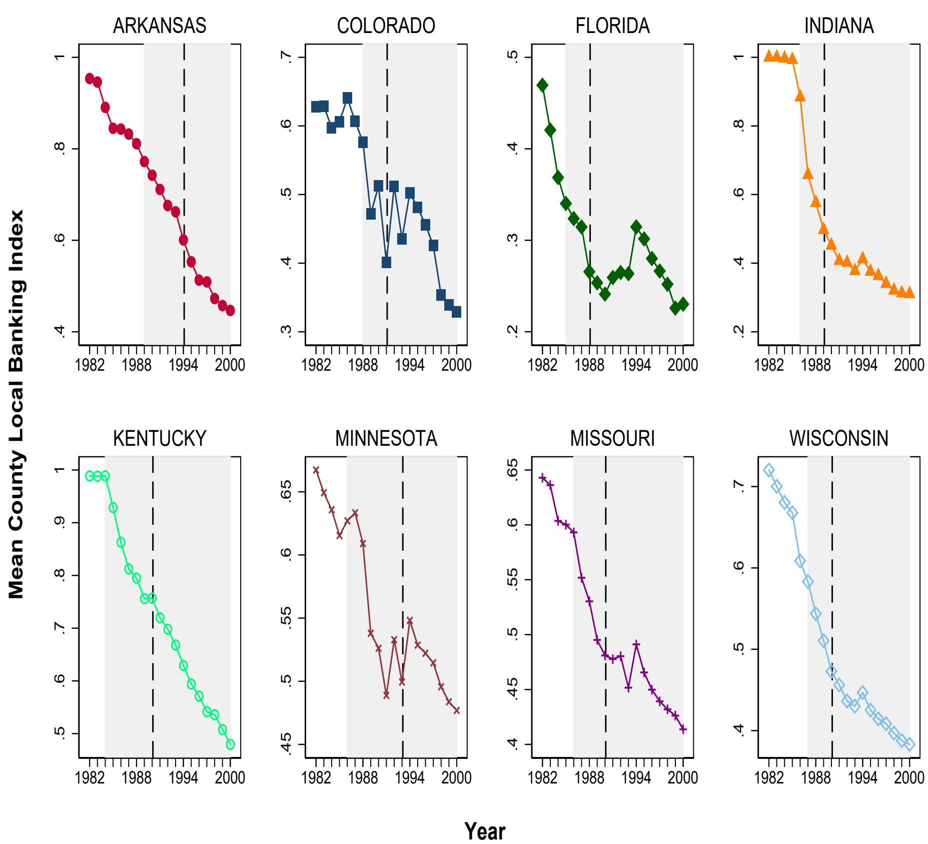
The table shows the coefficient estimates and standard errors for estimating Equation 2 using the predicted local lending ratio from Equation 3. The dependent variables are: ln total home loan dollars, ln employment rate, ln adult population, ln wage per capita. Significance level: *** 1%, ** 5%, * 10%. Data sources: CBP, FDIC, FEMA, HMDA, NBER, US BEA.

Figure 3: **State Banking Deregulation and Local Bank Index**

Panel A. Illinois and Arkansas 1982-2000

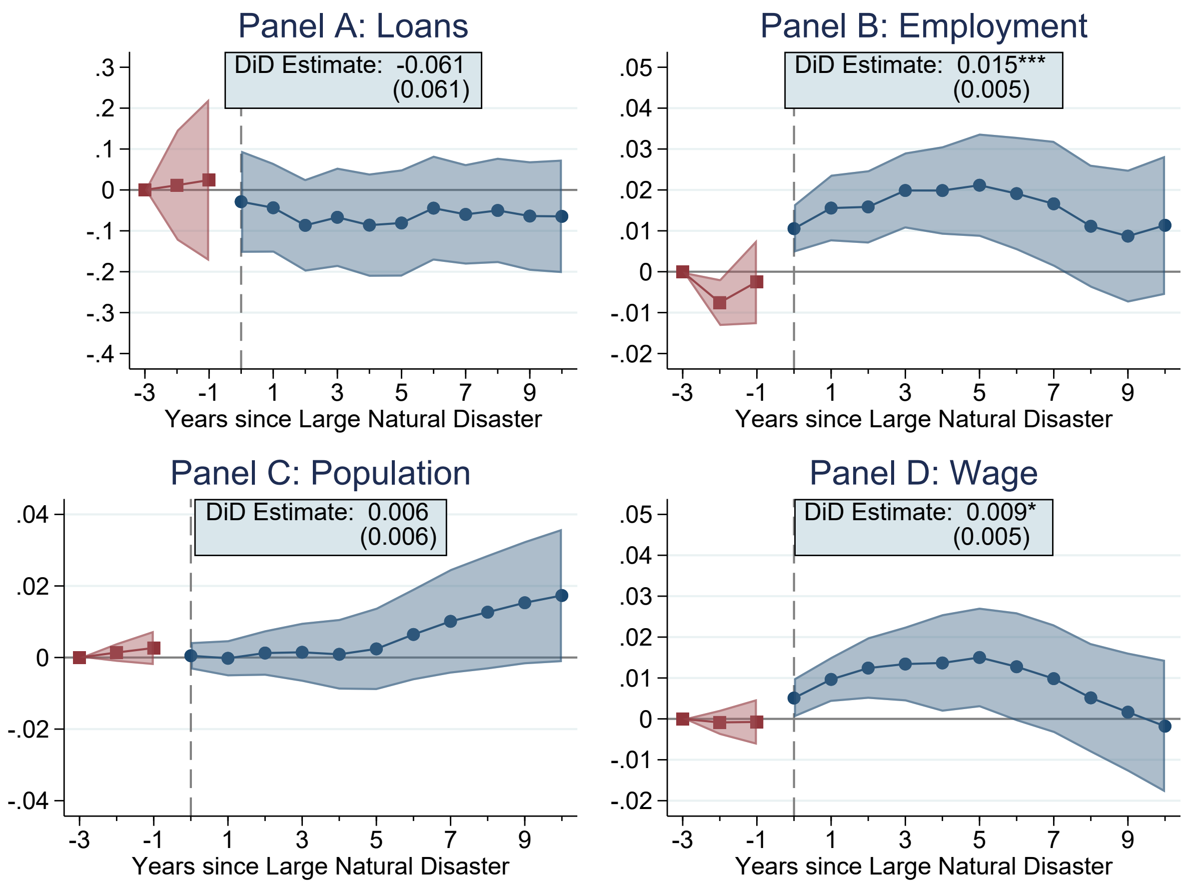


Panel B. States with Interstate Deregulation before Intrastate Deregulation



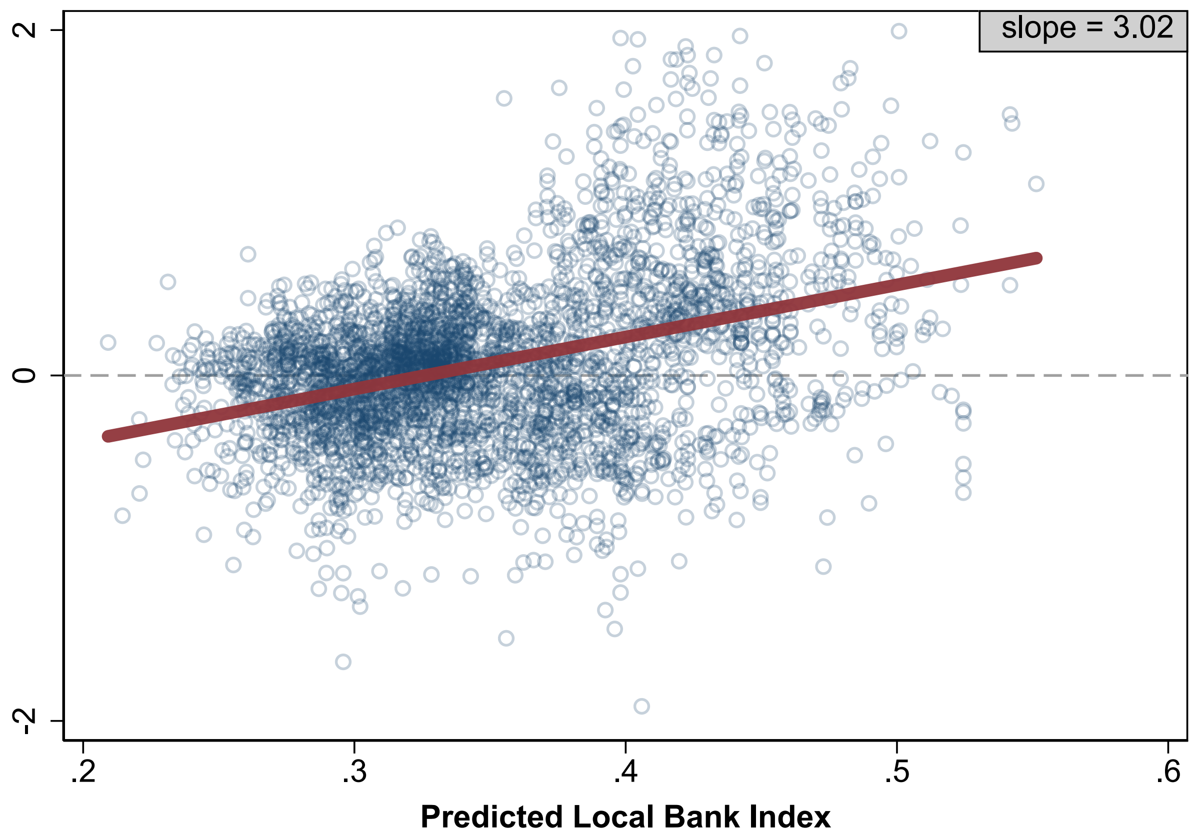
Panel A: The dark (light) dashed vertical lines represent the passage of *interstate* deregulation in Illinois (Arkansas). Panel B: The shaded regions indicate years with interstate deregulation, while the dashed line marks the year of intrastate deregulation. Data sources: FDIC.

Figure 4: **Overall Impact of a Large Natural Disaster**



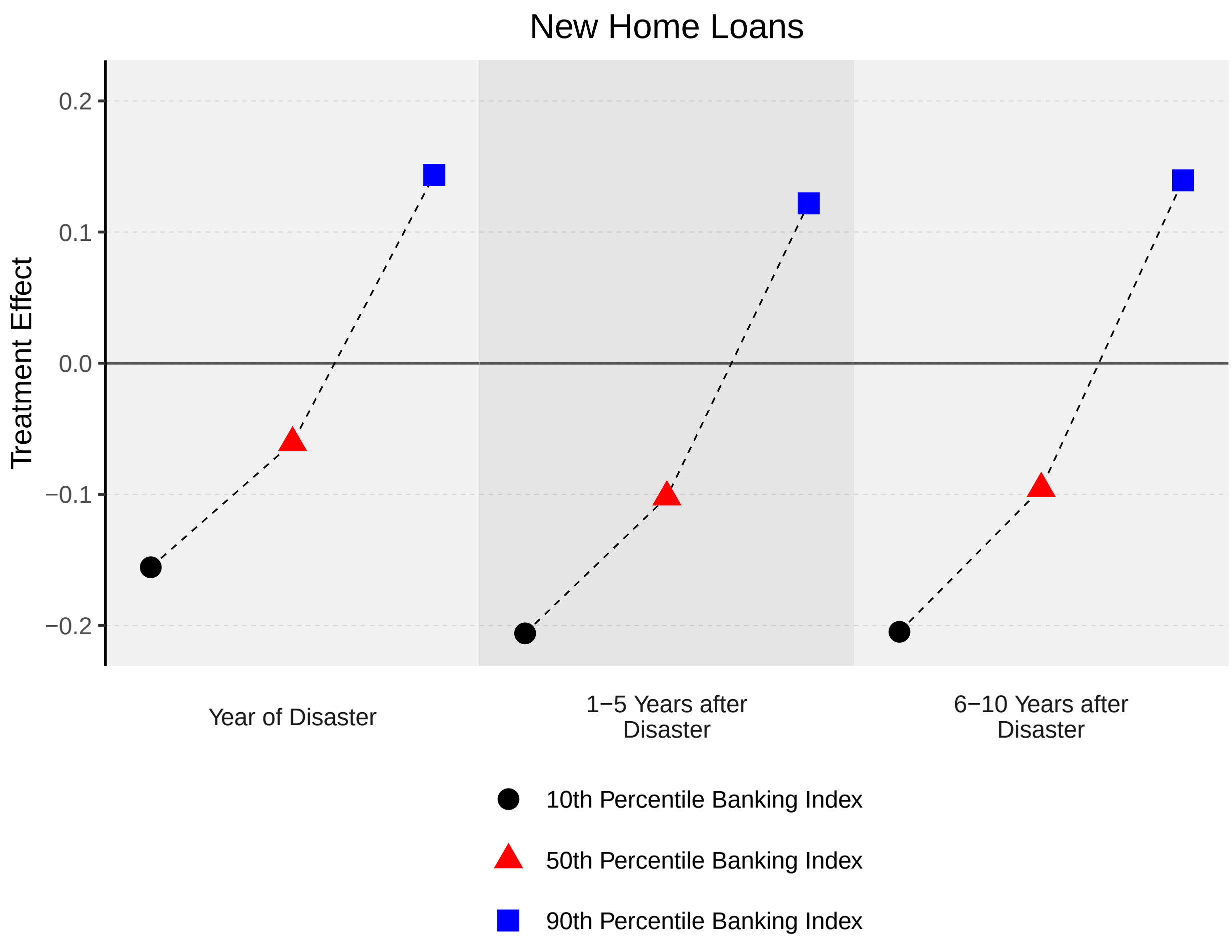
The figure plots the estimated coefficients from an imputation-based event study model that ignores differences in the composition of banking institutions (local versus non-local) in a county at the time of a large disaster. The figure plots the results for four outcomes: ln total home loan dollars (panel A), ln employment rate (panel B), ln adult population (panel C), ln wage per capita (panel D). Data sources: CBP, FDIC, FEMA, HMDA, NBER, US BEA.

Figure 5: **Difference in Loan Dollars in the Year following a Large Natural Disaster**



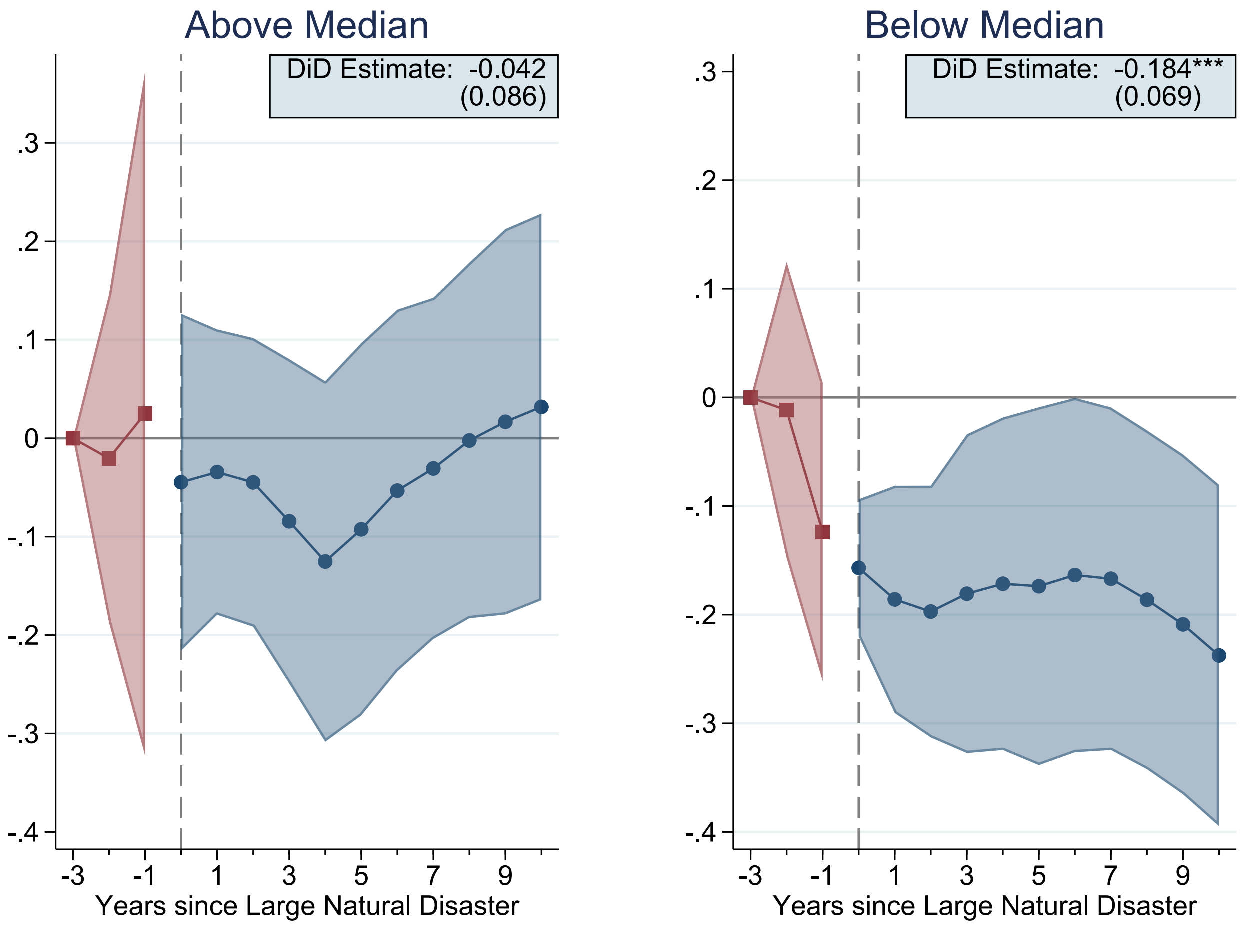
The figure plots the immediate change in ln loan dollars for new originations for all county years with a large disaster (1991-2013). The change in ln loan dollars is restricted to the interval [-2,2]. The slope of the best fit line is 3.17 when outliers are included. Data sources: FDIC, FEMA, HMDA.

Figure 6: **Home Loan Model Estimates by Level of the Local Banking Index**



The figure shows the implied effect on the change in new home loans using the estimated point estimate from Table 3. Data sources: FEMA, HMDA.

Figure 7: **New Home Loans following a Large Disaster by Local Bank Index**



The figure shows point estimates and 95% confidence intervals using the imputation-based model. We separately estimate the model for counties with an above median banking index at the time of a large disaster, and for counties with a below median banking index at the time of a large disaster. We include all of the control counties in each specification. The model is run with year fixed effects. Data sources: FEMA, HMDA.