

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, which is consistent with moral hazard concerns limiting credit availability. We instrument for the share of local banking at the time of a disaster using the timing of state-level deregulation, so as to isolate the role of bank type from the endogenous economic conditions that led to the development of banking institutions. We estimate a reduction in credit supply manifested by fewer new home loans in counties with a higher share of local banking at the time of the disaster. There is suggestive evidence that these same counties exhibit lower wages and population growth in the eight years following a large natural disaster.

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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 by shifting capital from other geographic regions in which they operate (e.g. Cortes and Strahan [2017]).

Community (or “local”) banks, by contrast, 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 when a natural disaster occurs have greater aggregate lending post-disaster? The degree of local lending may affect the cost of information acquisition, business incentives, and financial stability which 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?

The total amount of new credit provided by private banking institutions post-disaster is an important source of funding for disaster recovery. Moreover, 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 large 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 natural disaster. We use federal disaster assistance to repair public infrastructure as a proxy for disaster cost. This 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 county-level employment, wages, and population. Our preferred panel is from 1990-2006 and limits the analysis to flood-related Presidential Disaster Declarations (approximately 80% of all declarations).²

We estimate local projection (event study) 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

¹Another approach is to model the severity of the storm using meteorological information, rather than actual disaster cost (e.g. Deryugina [2017]). 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. Many researchers use disaster damage reported in the SHELDUS database (e.g. Cortes and Strahan [2017]). We do not use SHELDUS as a source of disaster damage, as Gallagher [2023] shows that SHELDUS suffers from a serious, non-random missing data problem.

²Flood-related disasters include those listed by FEMA as coastal storm, severe storm, hurricane, or flood. We discuss the data and modeling considerations that motivate this sample in Section 3.

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

We find that overall lending is around 5% lower in the years immediately following a large disaster, relative to the level of lending had there been no disaster. This result is consistent with moral hazard concerns reducing available credit to a region following a negative economic shock (e.g. Townsend [1979]; Holmstrom and Tirole [1997]). We estimate that there is lower credit, both fewer new loans and less loan dollars, for up to seven years following a disaster in the counties with a higher share of local banking at the time of the disaster. We find no difference in the overall level of new credit following a large disaster when we do not instrument for the endogenous development of banking institutions. Instrumenting for the market share isolates the credit-provision role of the banks from other local economic conditions.

Post-disaster county-level economic outcomes also differ based on the intensity of local banking at the time of a disaster. Overall, we find that wages and employment are higher for the six years following a large disaster. There is some evidence for a small and temporary reduction in population. Changes in wages are largest, and population loss smallest, in counties that have a higher instrumented non-local banking share at the time of the disaster. The increase in new lending in regions with more non-local lenders appears to contribute to a more robust short-term economic recovery from the disaster.

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.³

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 [2023]; 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. 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. 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.

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 of both screening and monitoring 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

³The existing literature is also limited in that Gallagher and Hartley [2017] only examine a single right-tail event. Their findings may not generalize. Cortes and Strahan [2017] consider a larger sample, but the identification strategy depends on disaster damage being reported in the SHELDUS database.

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 deviate from the model in two ways. First, Morgan et al. [2004] focus on a binary definition. The banking system is either interstate or not interstate. We hypothesize that the *degree* to which a region is exposed to interstate banking can determine whether, on net, credit to a disaster region increases or decreases post-disaster. Second, due to data constraints, we focus on that lending to homeowners rather than entrepreneurs.⁴ 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*, decrease 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 concerns 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*, increase 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 (e.g. Butler and Williams [2011]). The informational advantage in regions with a higher share of local banking will, *all else equal*, increase post-disaster lending as compared to regions with

⁴We show that there is a high correlation between these types of lending activity during the time period that we have data for both home and business loans.

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.⁵

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 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 identifiers 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:

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

LenderLocalness is defined as the total deposits by lender l in county c in year t , divided by the

⁵States 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]).

Table 1: **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).

total deposits held by that lender in year t . $LenderCountyShare$ 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 the total deposits in the county that are held by that lender. 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. We formally test how deregulation predicts the banking index in Section ??.

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.

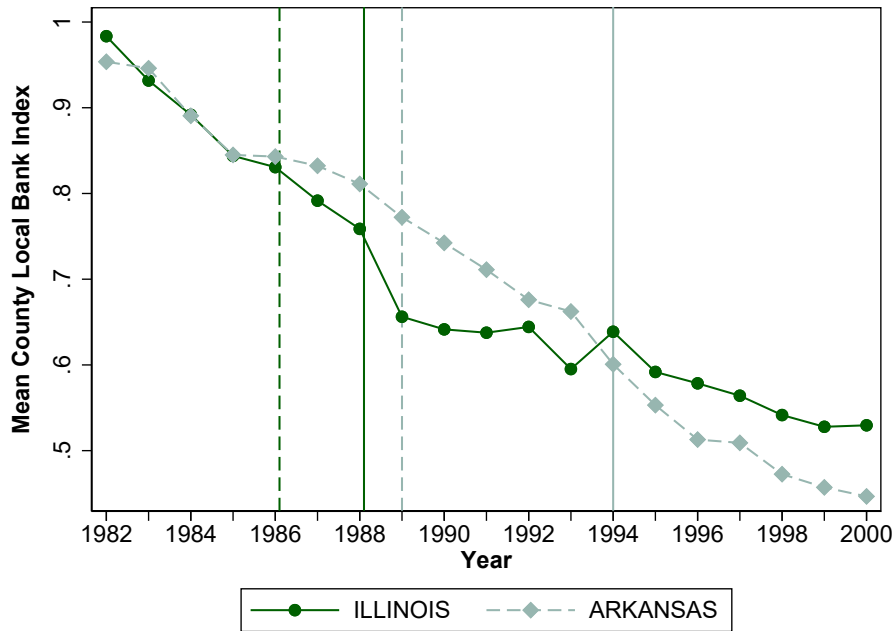
Panel B shows the mean county local bank index for the eight states where interstate deregulation occurred three or more years before intrastate deregulation. Five of the states (Colorado, Indiana, Kentucky, Minnesota, Missouri) exhibit a trend break at or just after the year of interstate deregulation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

2.3 Data Sources

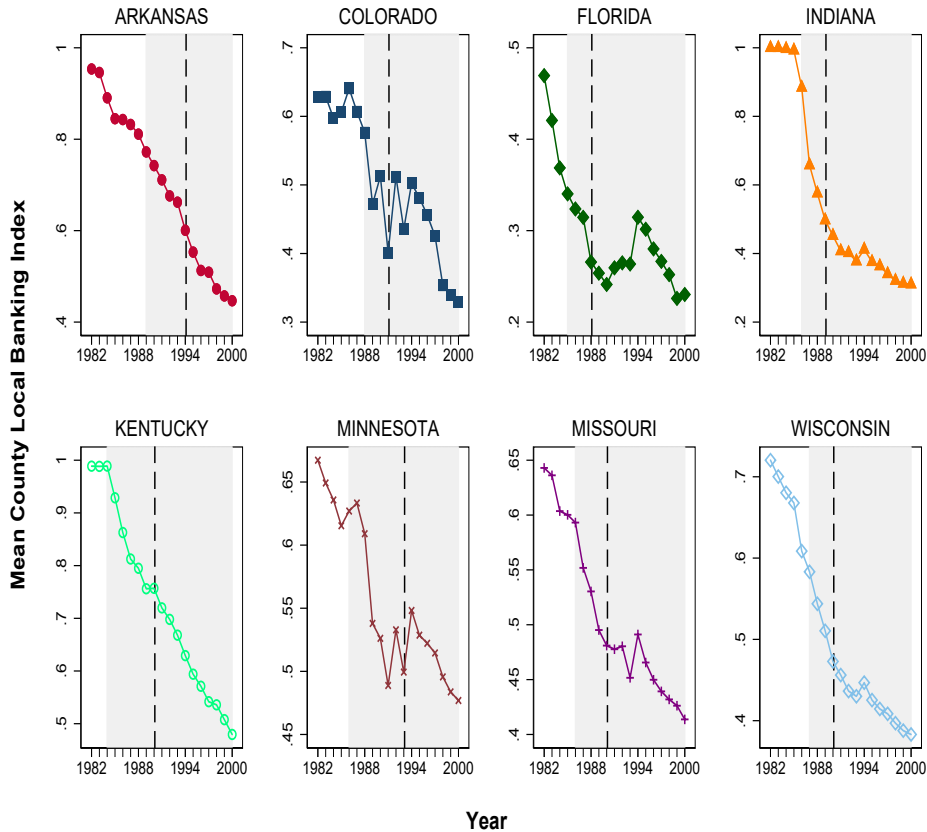
This subsection describes the data sources that we use except for the FDIC bank deposits data and the bank deregulation information which are described in Section 2.2.

Figure 1: 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 dashed (solid) vertical lines indicate passage of interstate (intrastate) deregulation. Panel B: The shaded regions indicate years with interstate deregulation, while the dashed line is intrastate deregulation. Data sources: FDIC.

2.3.1 Natural Disaster Incidence and Cost

The natural disaster data include all Presidential Disaster Declarations (PDDs) from 1981-2014. PDDs are approved state-by-state and include a list of counties affected by the disaster. All PDD counties (hereafter “disaster counties”) are eligible for federal assistance to repair public infrastructure. Public Assistance is available to local governments and non-profit organizations to repair infrastructure and to aid in the reconstruction of public buildings in disaster counties. Public Assistance is a consistent proxy for the cost of disaster damage over time, and avoids the missing data concerns associated with the commonly used SHELDUS weather damage database (SHELDUS [2020]). Missing data in SHELDUS are pervasive and nonrandom (Gallagher [2023]).

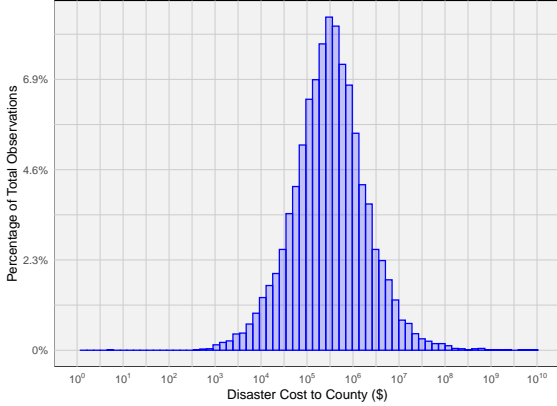
A drawback of the Public Assistance cost information is that the data are only publicly available at the disaster level (aggregated across counties) for most PDDs prior to the early 2000s. Figure 2 panel A shows that there is a large amount of variation in disaster damage among counties included in PDDs. Counties in the right tail of the disaster cost distribution can incur damage that is several orders of magnitude larger than the average disaster county. Moreover, Gallagher [2014] finds that only about one third of cities and towns in the typical flood-related Presidential Disaster county incur any disaster damage. We could divide the total amount of Public Assistance distributed for each PDD by the number of counties included in each PDD. However, this assigns equal damage to all counties included in the same disaster declaration and suffers from a high level of measurement error. Instead, we use county-level Public Assistance data from 1990-2006 obtained through a Freedom of Information Act Request (FOIA). One drawback is that these county-level data are only for flood-related PDDs (approximately 80% of all PDDs during this time period).⁶

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 HMDA 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

⁶These data were first used in Gallagher [2014]. Flood-related PDDs include those listed by FEMA as coastal storms, severe storms, hurricanes, and floods. Disaster cost and all other dollar-denominated variables are adjusted using the Consumer Price Index to real 2014\$.

Figure 2: Disaster Cost and Bank Lending Data



(a) Distribution of County Public Assistance



(b) New Home and Business Lending

Data sources: FEMA, FFIEC, HMDA.

Examination Council (FFIEC) and is available beginning in 1997. Both databases contain unique lender identification numbers 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. County-level home lending is highly correlated with business lending (see Figure 2 panel B).

HMDA also includes applicant income. We use applicant income to examine whether new credit is more restricted for lower income residents following a large disaster. Moreover, the composition of banking institutions in a disaster region could determine the distribution of credit in addition to the overall level of new lending. Local banks are often more willing to use “soft” information gained through relationship lending when making loan decisions (e.g. Berger and Udell [2002]; Hein et al. [2005]; Nguyen [2019]). As a result, lower income residents may be more likely to access credit following a disaster in regions that have a higher concentration of local banking (e.g. Mayer [2022]). We test for this using our statistical model.

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

3 Statistical Model

3.1 Estimation

The recent methodological literature on event studies has shown several potential limitations when two-way fixed effect models are estimated using ordinary least squares (OLS) (e.g. Borusyak et al. [2021]; Sun and Abraham [2021]). We estimate a linear projections difference-in-differences model (Dube et al. [2023]; Jorda [2005]; Tran and Wilson [2023]). The model allows us to estimate the impulse response function (IRF) for a large natural disaster on the regional economy, while controlling for other disasters in the county during the estimation horizon, h . Specifically, we estimate Equation 2 for all horizons $h = 0$ to $h = 8$, as well as, two pre-disaster horizons $h = -2$ and $h = -3$. We estimate the equation separately for each horizon.

$$\begin{aligned}
 y_{c,t+h} - y_{c,t-1} = & \sum_{\substack{\tau=-p \\ \tau \neq -1}}^h \beta_{\tau}^h 1[LargeDisaster_{c,t+\tau}] + \sum_{\substack{\tau=-p \\ \tau \neq -1}}^h \alpha_{\tau}^h 1[OtherDisaster_{c,t+\tau}] + \\
 & \sum_{k=1}^K \rho_k^h (y_{c,t-1} - y_{c,t-k}) + \lambda_c^h + \eta_t^h + \epsilon_{c,t}^h
 \end{aligned} \tag{2}$$

The dependent variable is the h period ahead lead of the logged outcome variable minus the logged outcome variable in $t - 1$, the reference period. y_{ct} is a local economic outcome, such as the dollar amount of new loans or the employment rate, in county c in year t . The model allows for disasters to have a different economic impact based on their magnitude, as measured by their cost. Our goal is to examine counties that experience a large financial shock, while still being able to estimate the statistical model with reasonable precision. 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. We control for disasters that occurred during the past five years ($p = 5$) and for disasters that occur within the estimation horizon.⁷

The coefficient of interest is β_0^h , the estimated impact of a large disaster on a local economic

⁷The *OtherDisaster* variable also includes non-flooding PDDs for which we don't have county-specific cost. Our baseline sample only includes county observations if there have been at least five years since the previous large disaster. The five year window is motivated by empirical evidence (see Section 3.2). We omit the lags for a *LargeDisaster* when running the model for our baseline sample. The choice of $p = 5$ matches that of Tran and Wilson [2023]. Estimates for our coefficient of interest are largely insensitive to the choice of p .

outcome h years after the disaster, relative to how the local economy would have evolved in the absence of a large disaster, and conditional on the other variables in Equation 2. One feature of the linear projections model is that we are able to control for lagged values of the dependent variable. Our baseline model controls for changes in the lagged dependent variable in the three years prior to a large disaster ($K = 3$). County fixed effects (λ_c) account for factors specific to a county that do not change during our panel (e.g. geographic location). Year fixed effects (η_t) flexibly control for common calendar time factors (e.g. economic conditions, population trends). We cluster the standard errors at the state by year level to allow for geographic correlation in the occurrence of a natural disaster.

Equation 3 extends Equation 2 to allow for heterogeneity in the 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]).

$$\begin{aligned}
y_{c,t+h} - y_{c,t-1} = & \delta^h 1[LargeDisaster_{c,t}] * LocalBanking_c + \gamma^h LocalBanking_c + \\
& \sum_{\substack{\tau=-p \\ \tau \neq -1}}^h \beta_\tau^h 1[LargeDisaster_{c,t+\tau}] + \sum_{\substack{\tau=-p \\ \tau \neq -1}}^h \alpha_\tau^h 1[OtherDisaster_{c,t+\tau}] + \\
& \sum_{k=1}^K \rho_k^h (y_{c,t-1} - y_{c,t-k}) \lambda_c^h + \eta_t^h + \epsilon_{c,t}^h
\end{aligned} \tag{3}$$

The δ^h are the coefficients of interest and measure how the impact of a large disaster varies post-disaster based on a region's banking institutions in the year before the large disaster. $LocalBanking_c$ is constructed using Equation 1. $LocalBanking_c$ is first set at the 1981 level for each county. 1981 is the first year that the bank deposits information is available and is also at the beginning of the bank deregulation period. $LocalBanking_c$ is fixed for the county and subsumed by the county fixed effects for those counties that never have a disaster (1990-2006). The value of $LocalBanking_c$ is reset at the level in the year before a large disaster for the remainder of the panel for those counties with one large disaster. $LocalBanking_c$ is again reset to the value in the year before any subsequent large disaster for those counties that experience multiple large disasters.

We instrument for bank localness by estimating Equation 4.

$$\begin{aligned}
LocalBanking_{ct} = & \gamma_1 1[Interstate_{ct}] + \gamma_2 1[Intrastate_{ct}] + \gamma_3 InterstateLag_{ct} + \gamma_4 IntrastateLag_{ct} \\
& + \sum_{\tau=-a}^b \beta_\tau 1[LargeDisaster_{c\tau}] + \sum_{\tau=-a}^b \alpha_\tau 1[OtherDisaster_{c\tau}] + \sigma_c + \phi_t + \nu_{ct} \quad (4)
\end{aligned}$$

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 exogenous deregulation variables are omitted from Equation 3. The other variables in Equation 4 are the disaster indicators (where the leads and lags match those in Equation 3), and county (σ_c) and year (ϕ_t) fixed effects. We cluster the standard errors at the state by year 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 preferred panel is an unbalanced 1990-2006 sample. There are four reasons why we focus on this time period. First, HMDA loan and county-specific FEMA disaster cost information are only available starting in 1990. Second, state-by-state bank deregulation occurs mostly in the mid-1980's to mid-1990's. We use the timing of deregulation to instrument for the level of local banking. In our view, the logic underpinning the instrument is less well supported once a state is several decades (or more) post-deregulation. Third, we end the panel in 2006 prior to the 2007 financial crisis and the Great Recession. The focus of our paper is on regional economic shocks. Limiting the analysis to before the Great Recession helps to avoid concerns that the financial crisis could

differentially impact how counties recover from an natural disaster. Fourth, non-bank mortgage lending increased dramatically following the Great Recession (e.g. Kim et al. [2022]). Our local bank index, constructed using bank deposits, is not as good of a measure of banking institutions beginning around 2007.

The panel is unbalanced for two reasons. There are a small number of counties with no reported bank deposits in some years. These observations are excluded. The larger reason is that our preferred specification assumes that the economic shock of a large natural disaster could persist for five years. Dube et al. [2023] emphasize that treatment effect in a linear projections difference-in-differences model (and in other event study models used in the literature) is only well-identified, in cases when there are multiple treatments for the same unit, when there is no longer any effect from the previous treatment. Our assumption of five years is based on estimating the economic outcomes using Equation 2. We estimate non-zero impacts for approximately five years. We note that our model estimates are very similar if we use a panel that does not drop any observations based on the timing since the last large disaster, or if we estimate a panel that drops observations based on a ten year window.

There are a total of 1,454 are flood-related disasters that exceed the 75th percentile cost threshold in our preferred sample (3% of the panel observations). We limit the post-disaster estimation horizon to eight years so that the entire impulse response function is identified by at least half of the large disasters in our sample. Thus, our model allows us to examine the short to medium-run impact of local banking institutions on credit provision and regional economic recovery following a large natural disaster.

4 New Lending following a Natural Disaster

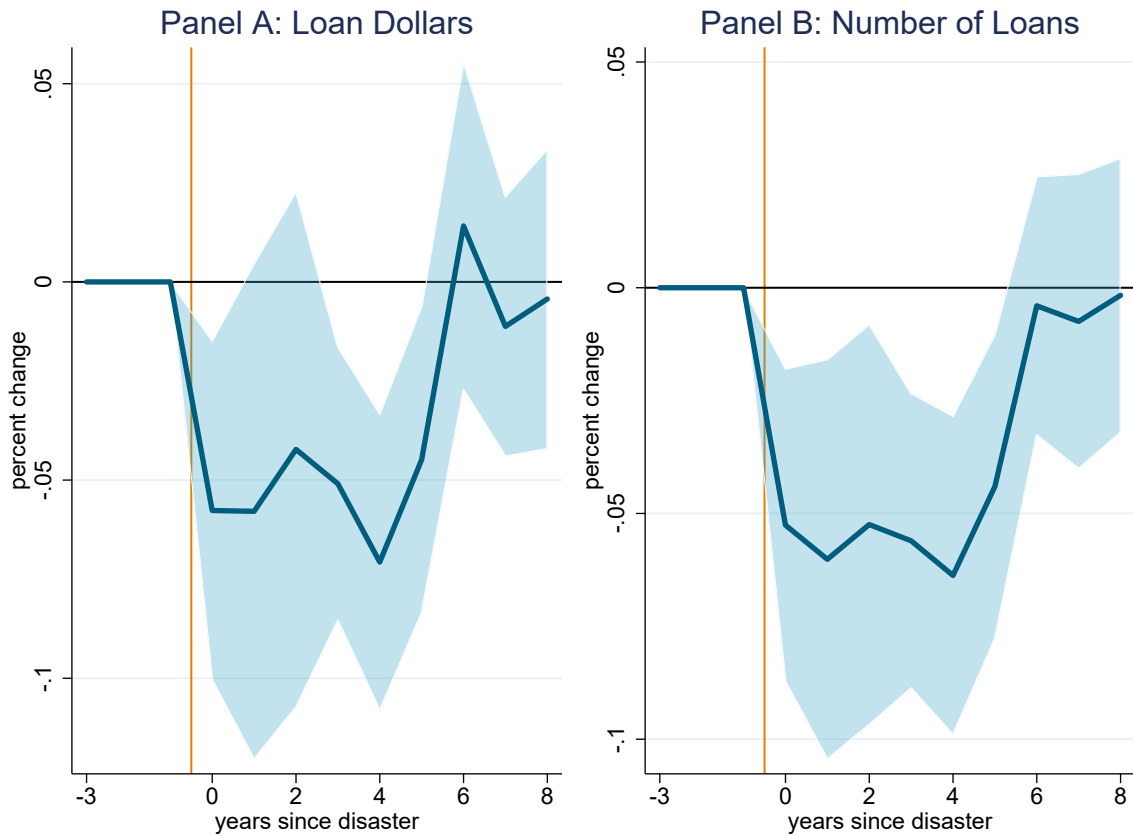
4.1 Overall Impact on New Lending

Figure 3 shows impulse response functions for the change in new home loans following a large disaster. We estimate the baseline model (Equation 2) that does not consider the level of local banking prior to the disaster. The IRF for the total dollar amount of new home loans (including lines of credit) is plotted in Panel A. We estimate that the dollar amount of new home loans is 5.8% (p-value = 0.008) lower in the year of a large disaster. The largest estimated effect, -7.1% (p-value

< 0.000), is four years following the disaster. We interpret this estimate as the average cumulative difference in new lending four years after the disaster, relative to the amount of new lending that would have occurred had the county never experienced the disaster. Panel B plots the IRF for the total number of new loans. The results are similar to those in Panel A. The impact on the number of new loans is again largest four years after the disaster.

Overall, we estimate that counties that experience a large natural disaster have an immediate reduction in new home lending of about 5%, relative to what would have occurred had there been no disaster. This reduction in bank credit persists for about five years in the disaster region.

Figure 3: **New Home Loans following a Large Disaster**



Notes: The figure plots two IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variables are \ln total loan amount (panel A) and \ln total number of loans (panel B). Data sources: FEMA, HMDA.

4.2 New Lending based on Pre-Disaster Local Banking Institutions

Our first main research question is whether there is greater post-disaster credit in locations with a higher share of local banking at the time of a natural disaster. We instrument for the level of local banking so as to isolate the causal role of banking institutions from the endogenous economic, socio-economic, and demographic conditions that led to the development of the banking institutions in a particular county.

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

Dependent Variable: County Local Banking Index			
Panel length:	<u>1981-2006</u>	<u>1990-2006</u>	<u>1990-2006</u>
	(1)	(2)	(3)
Intrastate Indicator	-0.147*** (0.012)	-0.090*** (0.031)	-0.090*** (0.030)
Interstate Indicator	-0.030** (0.015)	-0.090* (0.050)	-0.089* (0.050)
Intrastate Lag	0.005*** (0.002)	0.004*** (0.001)	0.005*** (0.001)
Interstate Lag	0.006* (0.003)	-0.057 (0.039)	-0.057 (0.039)
Disaster Indicators	X	X	X
County FE	X	X	X
Year FE	X	X	X
Drop Repeat Disaster Obs			X
R ²	0.747	0.806	0.805
Observations	74,411	51,356	49,722
F-Statistic, Regulation	66.3	6.0	5.7

Notes: The table shows the coefficient estimates and standard errors from estimating Equation 4 on our baseline panel (1990-2014). Standard errors are clustered state by year. Significance level: *** 1%, ** 5%, * 10%. Data Sources: FDIC, FEMA, Morgan et al. [2004].

Table 2 shows the results from estimating our instrumental variables model (Equation 4). We estimate the model on three panels. Column 1 displays results from estimating a 1981-2006 panel

that does not drop observations in counties where there are two disasters within five years. All four regulation variables are statistically significant. For example, we estimate that the county local banking index is 14.7 percentage points lower (p-value < 0.01) in the years following passage of intrastate deregulation. Recall that a lower index implies greater non-local banking. The deregulation variables remain strong predictors of the local banking index even after limiting the panel length to 1990-2006 and dropping observations if there are two large disasters within five years (column 3). Our preferred panel covers 1990-2006 for data and theoretical reasons (see Section 3.2). However, one disadvantage of the shorter panel is that we do not fully leverage the variation in state deregulation (see Table 1).⁸

Figure 4 plots the coefficient of interest from the model (Equation 3) where we estimate the differential impact of a large disaster on new lending based on the level of the local banking index in the year before the disaster. The coefficient of interest is the interaction term in the model (disaster indicator by level of banking index). Panel A shows the IRF when we instrument for the banking index. There is an immediate drop in the estimated coefficients that mirrors the overall reduction in lending in Figure 3. The coefficients remain negative throughout the post-disaster period and are statistically different from zero in five of the first seven years.

The negative interaction coefficients imply that counties with greater local banking (a higher banking index) at the time of a natural disaster have less lending post-disaster. The 25th and 75th quartiles of estimated banking index across all counties and years in our sample are 0.17 and 0.61, respectively. The estimated difference in new lending in counties at the first and third banking index quartiles in the four years post-disaster is: $(-0.25 * 0.17) - (-0.25 * 0.61) = 0.11$. Counties with a greater share of non-local banking (1st quartile) are estimated to have 11 percentage points more lending, as compared to those counties with a higher share of local banking (3rd quartile).⁹

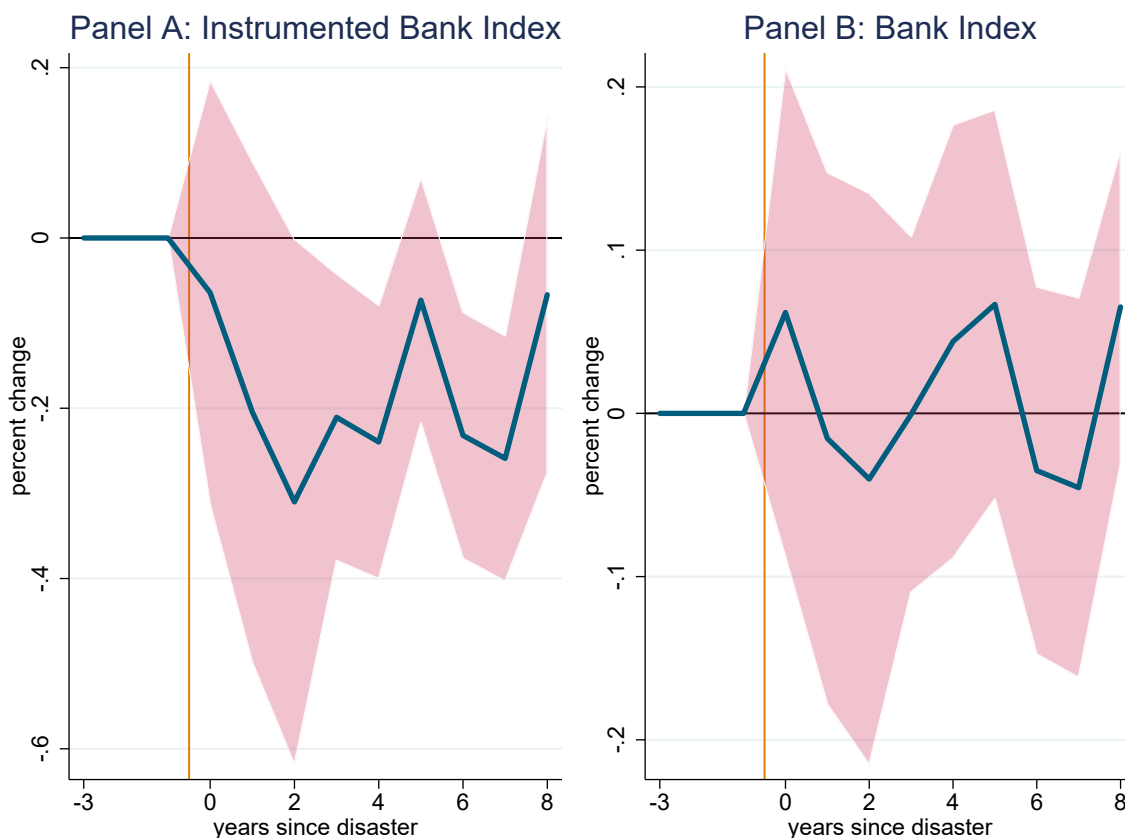
Panel B shows that the composition of local banking institutions has no estimated impact on post-disaster lending when we do not instrument for the endogenous development of these institutions. The estimated coefficients oscillate around zero and are not statistically different

⁸We are able to increase the F-statistic for the joint hypothesis that the deregulation variables are different from zero (to e.g. above 10) by extending the time period beyond 2006. Since we cluster state by year, and the default for the F-test is to use the number of clusters as the number of observations, increasing the panel length modestly increases the F-statistic.

⁹The estimated *overall* lending effect from this model is calculated as: $\hat{\beta}_\tau^h + \hat{\delta}^h * \widehat{LocalBanking}_c$. The estimated coefficients for a (non-interacted) Large Disaster, $\hat{\beta}_\tau^h$, are positive, but not statistically different from zero (except for six and seven years post-disaster).

from zero. Section 6 uses US Census data to explore how differences in county demographics and economic development could explain why instrumenting for the local banking index is important to isolate the role of local banking on post-disaster lending.

Figure 4: **New Home Loans after a Large Disaster by Level of the Local Banking Index**



The figure plots the local banking index by large disaster (interaction variable) point estimates and 95% confidence intervals from estimating Equation 3. The dependent variable is \ln total loan amount. The two panels differ by whether the model instruments for the local banking index. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004].

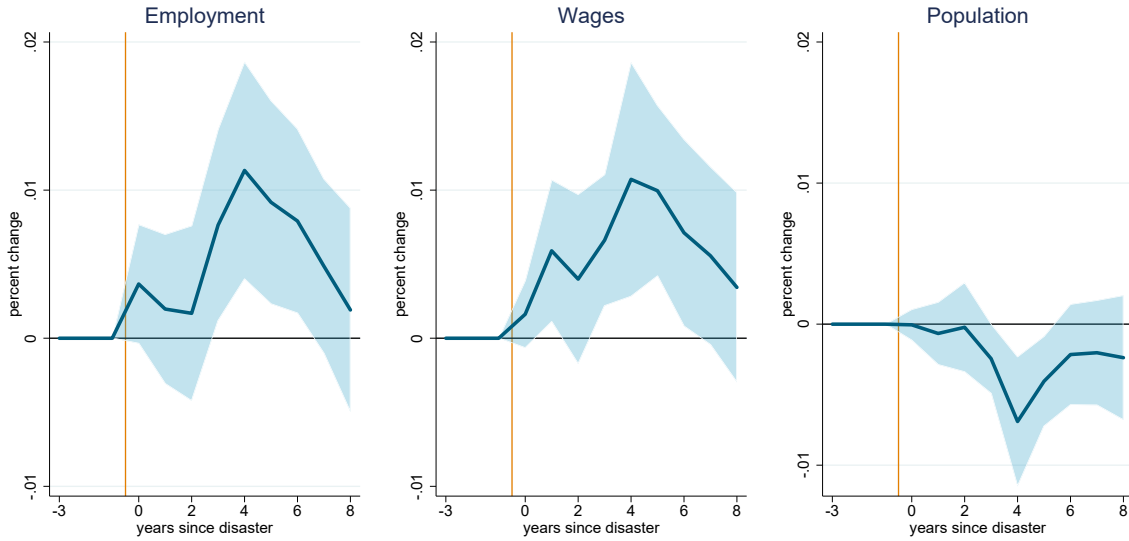
5 The Impact of Large Disasters on Local Economic Outcomes

We estimate the impact of a large natural disaster on the local economy in Figure 5 panel A. Wages and employment increase in disaster counties by around 1%. Our estimates are broadly consistent with Tran and Wilson [2023], although their estimates are somewhat larger. We find suggestive evidence for a small, temporary decrease in population of around 0.5%. The existing literature is mixed on how natural disasters affect local population growth. Boustan et al. [2012]

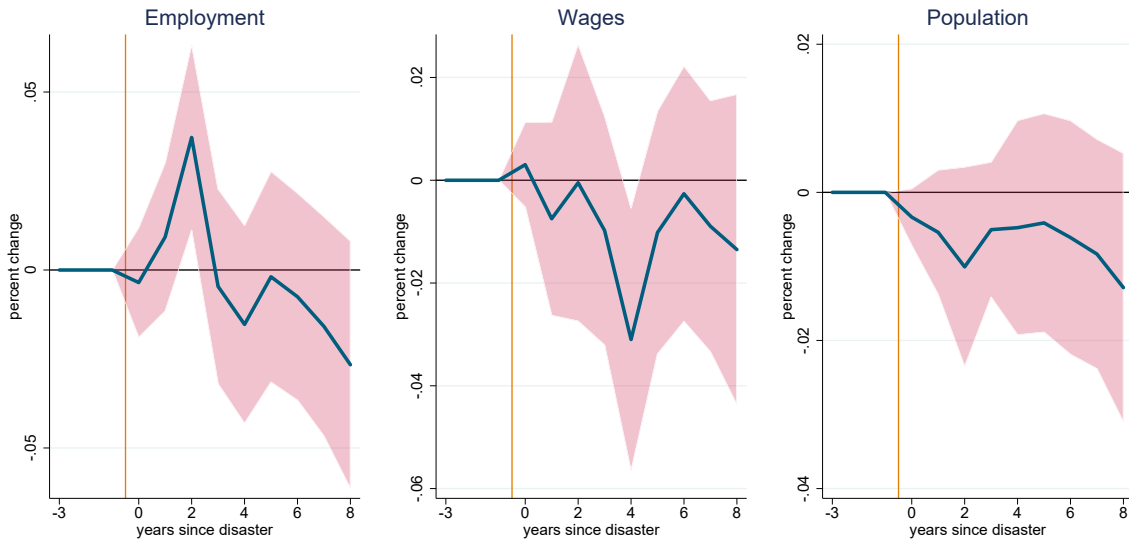
show that net out-migration increases following natural disasters in the US during the early 20th century. Deryugina [2017] and Tran and Wilson [2023] found no impact on future population growth following natural disasters in the US during the late 20th century.

Figure 5: **Local Economic Outcomes after a Large Disaster**

Panel A: Overall Impact



Panel B: Role of Local Banking



Panel A plots the estimated IRFs from three separate specifications of Equation 2 differ only by the dependent variable: In adult employment rate, In wages per capita, and In population. Panel B plots the interaction variable (local banking index by large disaster) coefficients from estimating Equation 3 for the same dependent variables, while instrumenting for the banking index. Data sources: Bureau of Economic Analysis, County Business Patterns, FDIC, FEMA, National Bureau of Economic Research.

Figure 5 panel B examines whether differences in post-disaster lending by the composition of local banking institutions impacts local economic outcomes. The sub-figures plot the estimated coefficient on the interaction variable (disaster indicator by level of banking index) in Equation 3. We instrument for the banking index. The IRFs do not provide conclusive evidence for how local banking institutions affect post-disaster economic recovery. Wage and population growth appear to be lower in counties with greater local banking, but the confidence intervals generally contain zero. At the same time, there is some evidence for a temporary spike in employment immediately following a disaster in counties with greater local banking.

6 Discussion

We show that new home lending (inclusive of home equity lines) decreases by about 5% for five years following a large natural disaster. Our empirical setting includes all flood-related Presidential Disaster Declarations 1990-2006. We define a large natural disaster as one that exceeds the 75th cost threshold. The reduction in lending is greater in counties with a higher share of local banking at a time the large disaster. We identify the causal role of local banking on post-disaster credit by instrumenting for the share of local banking at the county-level using the timing of state deregulation.

We estimate a small improvement in the local economy for disaster counties in the six years following a large disaster. There is a temporary boost in employment and wages of around 1%. There is also suggestive evidence for a very small and temporary decrease of 0.25%-0.5% in the population of disaster counties for several post-disaster years. The impact that local banking institutions have on economic recovery in a disaster county is less clear. There is suggestive evidence that wages and population are lower post-disaster in counties with a higher share of local banking. At the same time, there appears to be an immediate boost in employment post-disaster in these same counties.

Later drafts of this manuscript will seek to augment our findings in two ways. First, we plan to use income information reported in HMDA to examine whether the composition of local banking affects the distribution new loans. For example, locally focused banks may be more willing to lend to lower income residents following the disaster. Second, we plan to use socio-economic and

demographic information from the US Census to shed light on how instrumenting for the bank index allows us to separately identify the role that banks have in post-disaster recovery from that of other factors that may affect a county's economic recovery.

7 References

- Spatial hazards events and losses database for the united states metadata. Technical report, Arizona State University, June 2020. URL <https://cemhs.asu.edu/sheldus/metadata>.
- Federal Emergency Management Agency. Declared disasters. Technical report, 2019. URL <https://www.fema.gov/disasters/disaster-declarations>.
- Allen N. Berger and Gregory F. Udell. Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, 112:32–53, February 2002.
- Hoyt Bleakley and Jeffery Lin. Portage and path dependence. *Quarterly Journal of Economics*, 127:587–644, 2012.
- Kirill Borusyak, Xavier Jaravel, and Jann Spiess. Revisiting event study designs: Robust and efficient estimation. *Working Paper*, 2021.
- Leah Platt Boustan, Matthew E. Kahn, and Paul W. Rhode. Coping with economic and environmental shocks: Institutions and outcomes. *American Economic Review Paper and Proceedings*, 102(3), 2012.
- Leah Platt Boustan, Matthew E. Kahn, Paul W. Rhode, and Maria Lucia Yanguas. The effect of natural disasters on economic activity in u.s. counties: A century of data. *Journal of Urban Economics*, 118, 2020.
- Laurens M. Bouwer, Ryan P. Crompton, Eberhard Faust, Peter Hoppe, and Roger A. Pielke Jr. Confronting disaster losses. *Science*, 318:753, 2007.
- Bob Butler and Jessica Williams. One homeowner’s travails: Even after more than six years, family can’t move back into “new” house. *The Lens*, December 2011. URL <https://thelensnola.org/2011/12/23/kisa-holmes-six-years-later>.
- Brantly Callaway, Andrew Goodman-Bacon, and Pedro H.C. Sant’Anna. Difference-in-differences with a continuous treatment. *Working Paper*, 2021.
- David Card. Using regional variation in wages to measure the effects of the federal minimum wage. *Industrial and Labor Relations Review*, 46(1), 1992.
- Eduardo Cavallo, Sebastian Galiani, Ilan Noy, and Juan Pantano. Catastrophic natural disasters and economic growth. *The Review of Economics and Statistics*, 95(5), 2013.

- Matthieu Chavaz. Dis-integrating credit markets: diversification, securitization, and lending in a recovery. *Bank of England Staff Working Paper*, (617), September 2016.
- Benjamin L. Collier and Volodymyr O. Babich. Financing recovery after disasters: Explaining community credit market responses to severe events. *Journal of Risk and Insurance*, 86:479–520, 2019.
- Kristle Romero Cortes and Philip E. Strahan. Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1):182–199, July 2017.
- Yuliya Demyanyk, Charlotte Ostergaard, and Bent E. Sorensen. U.s. banking deregulation, small businesses, and interstate insurance of personal income. *The Journal of Finance*, 62(6):2763–2801, 2007.
- Tatyana Deryugina. The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3), 2017.
- Arindrajit Dube, Daniele Girardi, Oscar Jorda, and Alan M. Taylor. A local projections approach to difference-in-differences event studies. *NBER Working Paper*, April 2023.
- Federal Deposit Insurance Corporation. Fdic community banking survey. December 2012. URL <https://www.fdic.gov/regulations/resources/cbi/report/cbi-full.pdf>.
- Chao Fu and Jesse Gregory. Estimation of an equilibrium model with externalities: Post-disaster neighborhood rebuilding. *Econometrica*, 87(2):387–421, 2019.
- Justin Gallagher. Learning about an infrequent event: Evidence from flood insurance take-up in the us. *American Economic Journal: Applied Economics*, 6(3):206–233, 2014.
- Justin Gallagher. Retrospective voting and natural disasters that cause no damage: Accounting for the selective reporting of weather damage. *Working Paper*, January 2023. URL https://justingallagher.com/pdfs/Attentive_Electorate_012023.pdf.
- Justin Gallagher and Daniel Hartley. Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, 9(3):199–228, 2017.
- Edward Glaeser. Cities, productivity, and quality of life. *Science*, 333:592–594, July 2011.
- Scott Hein, Timothy W. Koch, and Steven Scott MacDonald. On the uniqueness of community banks. *Economic Review*, 90:15–36, 2005.
- Bengt Holmstrom and Jean Tirole. Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of economics*, 112(3):663–691, 1997.

- Solomon Hsiang and Amir S. Jina. The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. *NBER Working Paper*, (20352), 2014.
- Jith Jayaratne and Philip E. Strahan. The finance-growth nexus: evidence from bank branch deregulation. *Quarterly Journal of Economics*, 1996.
- Christian Johnson and Tara Rice. Assessing a decade of interstate bank branching. *Federal Reserve Bank of Chicago*, (3), 2007.
- Oscar Jorda. Estimation and inference of impulse response by local projections. *The American Economic Review*, (1), 2005.
- You Suk Kim, Karen Pence, Richard Stanton, Johan Walden, and Nancy Wallace. Non-bank and mortgage securitization. *Annual Review of Financial Economics*, 14, 2022.
- Patrick Kline and Enrico Moretti. Local economic development, agglomeration economies and the big push: 100 years of evidence from the tennessee valley authority. *Quarterly Journal of Economics*, 129(1):275–331, 2014.
- Howard Kunreuther, Erwann Michel-Kerjan, and Nicola Ranger. Insuring future climate catastrophes. *Climatic change*, 118(2):339–354, 2013.
- Stephanie Lackner. Earthquakes and economic growth. *FIW Working Paper*, (190), January 2019.
- Ross Levine, Chen Lin, and Wensi Xie. Geographic diversification and banks' funding costs. *Management Science*, July 2020.
- Erik J. Mayer. Big banks, household credit access, and intergenerational economic mobility. *SMU Cox School of Business Research Paper*, (21-04), 2022. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3816308.
- Donald Morgan, Bertrand Rime, and Philip E. Strahan. Bank integration and state business cycles. *Quarterly Journal of Economics*, 119(4):1555–1584, 2004.
- Patrick Mulloy and Cynthia Lasker. The rieggle-neal interstate banking and branching efficiency act of 1994: Responding to global competition. *Journal of Legislation*, 21:255, 1995.
- National Oceanic and Atmospheric Administration. Billion-dollar weather and climate disasters: Time series. 2020. URL <https://www.ncdc.noaa.gov/billions/time-series>.

- Hoai-Luu Q. Nguyen. Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics*, 11(1):1–32, 2019.
- Christina Paxson and Cecilia Elena Rouse. Returning to new orleans after hurricane katrina. *American Economic Review Papers and Proceedings*, 98:38–42, 2008.
- Tara Rice and Philip E. Strahan. Does credit competition affect small-firm finance? *The Journal of Finance*, 65(3):861–889, 2010.
- Michael Rothschild and Joseph Stiglitz. Equilibrium in competitive insurance markets: An essay in the economics of imperfect information. *The Quarterly Journal of Economics*, 80:629–649, 1976.
- Joseph Schumpeter. *The Theory of Economic Development: An Inquiry into Profits, Capital, Interest, and the Business Cycle*. Oxford University Press, 1969.
- Andrew Michael Spence. Job market signaling. *The Quarterly Journal of Economics*, 87:355–374, 1973.
- Erik Strobl. The economic growth impact of hurricanes: evidence from us coastal counties. *The Review of Economic Statistics*, 93(2), 2011.
- Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 2021.
- Robert Townsend. Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory*, 21:265–93, 1979.
- Brigitte Roth Tran and Daniel J. Wilson. The local impact of natural disasters. *Federal Reserve Bank of San Francisco Working Paper*, February 2023.