Natural Disasters, Local Bank Market Share, and Economic Recovery

Justin Gallagher and Daniel Hartley

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Abstract

US Interstate bank deregulation during the 1980s and 1990s led to larger, nationally diversified banks, and a decline in the number of local community banks. Economic theory suggests that community 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 there are differences in post-disaster credit allocation and regional redevelopment based on the concentration of local banking at the time of an economic shock. We find causal evidence of less credit allocated and somewhat weaker redevelopment in regions with more local banking.

JEL Codes: G21, O16, Q54, R11

Keywords: banking, deregulation, natural disasters

*Email: *justin.gallagher1@montana.edu*, *daniel.a.hartley@chi.frb.org* We thank seminar participants at the 2019 AERE summer conference, 2020 AEA meetings, the Federal Reserve Bank of Chicago regional/micro seminar, the 2021 PERC summer workshop, the 2022 NBER Summer Institute, the 2023 Federal Reserve Community Banking Conference, and the 2023 Climate Risk Management Conference at Georgia State University for valuable feedback. A special thanks to Benjamin Collier, Ivan Ivanov, Stephen A. Karolyi, and Philip E. Strahan for detailed feedback. We thank Brigitte Roth Tran and Daniel J. Wilson for generously sharing their local projection script, Stephen A. Karolyi for sharing deregulation information, and Taylor Begley and Umit Gurun for sharing SBA disaster loan data. Gallagher thanks the Initiative for Regulation and Applied Economic Analysis for research support. The opinions expressed are those of the authors and do not necessarily represent the views of the Federal Reserve Board of Chicago or the Board of Governors of the Federal Reserve System. Taurey Carr, Elainia Gupta, Joseph Knappenberger, and Kyle Musser provided outstanding research assistance.

1 Introduction

Over the past few decades the frequency and severity of natural disasters have increased. During the same period, bank deregulation has drastically diminished the role of community banks. Community banks have the potential to be key providers of liquidity in the wake of a large disaster due to their use of soft information to discern credit risk at a time when collateral may be damaged and their incentive to see the region that they serve rebound. At the same time, community banks may have less capacity to lend after large disasters if they are unable to raise capital. Do community banks play a unique role in lending in the wake of natural disasters? How has the decline of community banking affected post-disaster recovery and economic growth?

Prominent arguments for interstate deregulation in the 1980s and 1990s included that larger, nationally diversified US banks would lead to faster economic growth (e.g. Schumpeter [1969]) and improved economic stability (e.g. Demyanyk et al. [2007]). The reasoning was that 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]). On the other hand, a reduction in borrower collateral (e.g. home and auto values) 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. In constrast, community (or "local") banks focus on local lending and have relatively few total assets (FDIC [2012]). Economic theory suggests that, while community banks may have less *capacity* to lend 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]). Moreover, survey-based evidence suggests that firms may be more likely to have their credit needs met during an economic downturn when there are more community banks operating in the region (Berger et al. [2017]).

We find that there is less new credit allocated in counties with an higher share of local banking at the time of a natural disaster. We estimate the effects of exogenous variation in local banking shares induced by a deregulation instrument using new local projections difference-in-differences methods (Dube et al. [2023]). The total amount of new credit provided by private banks is an important source of funding for disaster recovery. We show new evidence that the *type* of banking institution affects post-disaster credit availability.

Specifically, 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 banking 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?

We calculate the total amount of new credit provided by private banking institutions as the dollar amount of new mortgage credit (including home equity loans). The amount lent by private banking institutions is two orders of magnitude larger than the federal disaster assistance provided to disaster-affected residents. Moreover, aggregate credit post-disaster could determine longer-run regional economic development if initial reinvestment affects the path dependence of future economic growth (e.g. Kline and Moretti [2014]), there are economies of agglomeration (e.g. Glaeser [2011]; Bleakley and Lin [2012]), 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. Paxson and Rouse [2008]; Fu and Gregory [2019]). 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. This setting provides an ideal test of the role of local banks when liquidity the most. 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 [2023]).

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] Our database includes information on nearly all new home (1990-2014) and business (1997-2014) loans. The 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).

We estimate 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. Our baseline model is a local projections difference-in-differences model, which is robust to many of the critiques of the recent difference-in-differences literature (Borusyak et al. [2021], Abraham and Sun [Forthcoming]). 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 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 state-level banking deregulation. The timing of state-level deregulation does not depend on state economic conditions or state banking profitability (e.g. Jayaratne and Strahan [1996]; Bisetti et al. [2020]; Levine et al. [2020]) and strongly predicts the concentration of local banking. We show that the instrumented bank index is uncorrelated with key socioeconomic variables.

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. The reduction in credit is more precisely estimated and slightly larger for low income individuals. These findings are consistent with asymmetric information 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

[1] We do not use disaster damage reported in SHELDUS, as is common among researchers studying natural disasters. Gallagher [2023] shows that SHELDUS suffers from a serious, non-random missing data problem. Using meteorological information, rather than actual disaster cost, is another approach to model the severity of a natural disaster (e.g. Billings et al. [2022]; Deryugina [2017]; Gallagher and Hartley [2017]; Gallagher et al. [2023]). However, 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.

a reduction in credit–fewer new loans, less loan dollars, and less loan dollars per capita–for up to seven years following a disaster in the counties with a *higher* instrumented share of local banking at the time of the disaster. The reduction in credit in counties with greater local banking is (again) more precisely estimated and slightly larger for low income individuals. Instrumenting for the market share isolates the credit-provision role of the banks from other local economic conditions. 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.

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]; Cortes and Strahan [2017]; Gallagher and Hartley [2017]; Collier and Babich [2019]). 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.[2]

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. Strobl [2011]; Boustan et al. [2020]; Roth Tran and Wilson [2023]) 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

[2]The 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 focus on a different question using the disaster damage being reported in the SHELDUS database.

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 has 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. Townsend [1979]; Holmstrom and Tirole [1997]; Morgan et al. [2004]).

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]; Berger et al. [2017]; 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 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 lending to households rather than entrepreneurs.[3] 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 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 (FDIC [2012]). At the same time, locations with a larger or wealthier population may be more able to cope with the

[3] We show that there is a high correlation between these types of lending activity during the time period where we have data on both home and business loans.

negative economic shock of a natural disaster (e.g. Lackner [2019]; Roth Tran and Wilson [2023]). 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 follows Morgan et al. [2004], while incorporating the updated deregulation dates in Bisetti et al. [2020].

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. Interstate banking and intrastate banking involve acquiring new charters.

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 intrastate banking in the form of 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 New York also passed an interstate reciprocity agreement in 1982. Interstate or intrastate deregulation was passed by at least one state in each year 1980-1994 (see Table 1).

Table 1: **Banking Deregulation by Year**

Deregulation Year	States Enacting Deregulation: Interstate Entry	States Enacting Deregulation: Intrastate
Pre-1980	0	18
1980	0	1
1981	0	2
1982	2	1
1983	2	1
1984	2	1
1985	12	4
1986	8	1
1987	10	5
1988	6	6
1989	2	1
1990	1	4
1991	2	2
1992	1	0
1993	1	1
1994	0	1

Data sources: Morgan et al. (2004); Bisetti et al. (2020).

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] Bisetti et al. [2020] emphasize that state-level interstate deregulation is not always reciprocal. For example, Alabama allowed out-of-state bank entry in 1987, while Alabama banks were able to enter at least one other state beginning in 1982. We follow Bisetti et al. [2020] and code the timing of interstate deregulation as the year when a state allows entry of out-of-state banks.

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. Morgan et al. [2004]; Jayaratne and Strahan [1996]; Bisetti et al. [2020]; Levine et al. [2020]). We show that the predicted level of local banking in a county, using deregulation as an instrument, is uncorrelated with key socioeconomic variables (see Section 4 and Table 3).

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:

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

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. *LenderCountyShare* is the total deposits by lender

[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 by the 1994 law (e.g. Rice and Strahan [2010]).

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 panel A shows a US county map displaying the level of the local banking index in 1995. We group counties by terciles of the banking index. The map illustrates the high degree of within state correlation in the local banking index. The map does not include state boundaries, yet using the county-level bank index we can nearly trace out the precise western boundaries for Montana, Wyoming, Colorado, and New Mexico. Counties in these states tend to have bank indices in the 2nd (yellow) and 3rd (red) terciles, while counties in states farther west have less local banking.

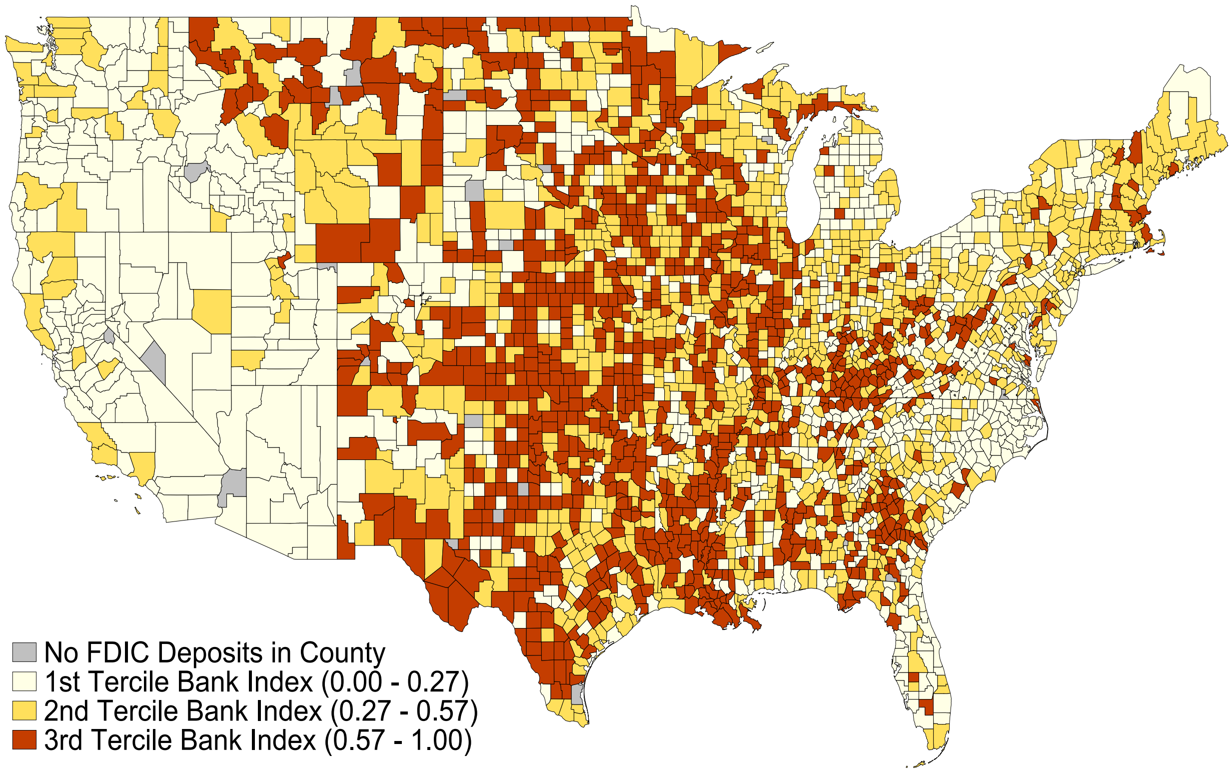
Figure 1 panel B shows how bank deregulation can be used to isolate plausibly exogenous variation in the intensity of local banking. We plot the mean county bank index for Illinois (circles) and Arkansas (diamonds) from 1982-2000. The dashed vertical lines mark the year that each state passed *interstate* 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. We formally test how deregulation predicts the banking index in Section 4.2.

2.3 Data Sources

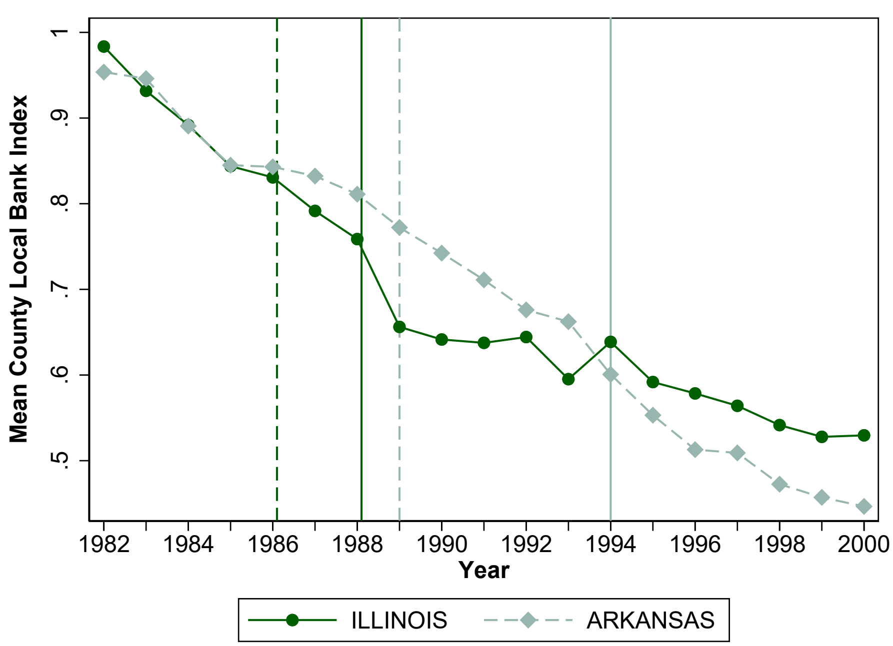
This subsection describes the data sources that we use except for the FDIC bank deposits data and the bank deregulation information which are described in Section 2.2.

Figure 1: **The Local Bank Index and State Banking Deregulation**

Panel A. Local Banking Index, 1995



Panel B. Illinois and Arkansas 1982-2000



Notes: The dashed (solid) vertical lines in Panel B indicate passage of interstate (intrastate) deregulation. Data sources: FDIC; Morgan et al. (2004); Bisetti et al. (2020).

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. 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]).

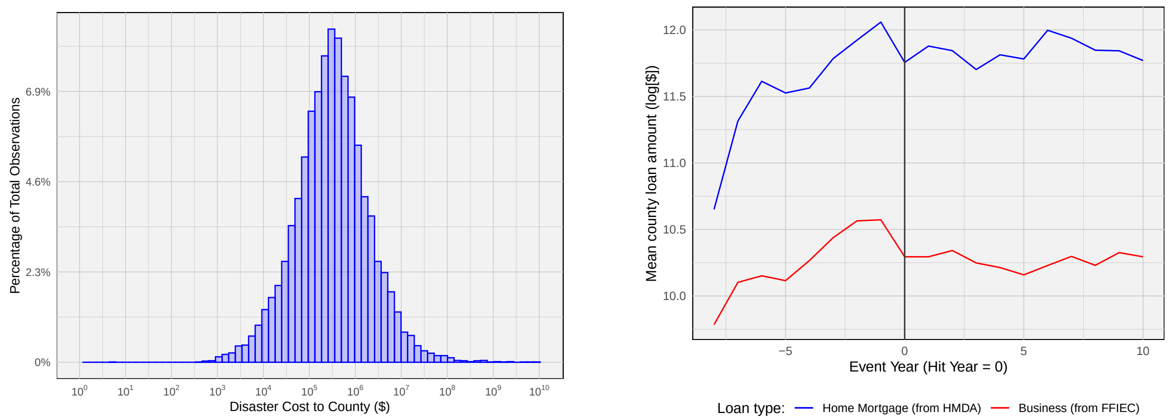
We use county-level Public Assistance data from 1990-2006 obtained through a Freedom of Information Act Request (FOIA). These data are geographically more precise than the publicly available information accessible through the databases linked to FEMA's website. Only disaster-level (aggregated across counties) Public Assistance information is available 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. The goal of this paper is to evaluate bank lending and regional economic outcomes following a large natural disaster. The advantage of using the county-level data is that we can examine counties in the right tail of the disaster cost distribution that incur damage that is several orders of magnitude larger than the average disaster county. One drawback is that these county-level data are only for flood-related PDDs (approximately 80% of all PDDs during this time period).[5]

2.3.2 Bank Loans, Direct Federal Disaster Assistance, and Regional Economic Information

There are two sources for (private sector) 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

[5]These 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 dollars.

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.

Federal Financial Institutions 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. Both measures of credit are increasing in counties that are later hit by a disaster, and then decrease for at least the first five post-disaster years (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. 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.

We use information on loan delinquency from the Federal Reserve Bank of New York Equifax Consumer Credit Panel (Equifax CCP) to partially test the hypothesis that local banks are better able to assess credit risk (e.g. Berger et al. [2005]). Detailed knowledge of the local economy (e.g. neighborhood-level home price trends) and soft information on loan applicants may allow local banks to do a better job at evaluating default risk, relative to national lenders, following a large economic shock.

Small Business Administration (SBA) disaster loans and FEMA Individual Assistance grants are the two main sources of direct federal disaster assistance. We use SBA disaster loan and Individual Assistance grants to assess the extent to which federal assistance crowds out private lending following a disaster. The SBA data were first compiled by Begley et al. [2024] via a FOIA request.[6] The Individual Assistance data were first compiled by Gallagher [2014] via a FOIA request.

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.

Appendix Table 5 lists all of the data sources. Appendix Table 6 provides summary statistics for variables in our analysis.

3 Statistical Model

3.1 Estimation

The recent methodological literature on staggered difference-in-differences 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]). Staggered difference-in-differences models can be biased when already treated units have lagged treatment effects and when these units are used as part of the control group for later-treated units. To address these limitations, we estimate a linear projections difference-in-differences model (LPDiD) (Jorda [2005]; Dube et al. [2023]; Roth Tran and Wilson [2023]). The LPDiD estimator avoids the potential bias described above by requiring the researcher to restrict the estimation sample to accommodate lagged treatment effects of a fixed length. In its baseline form the LPDiD estimator is equivalent to a stacked difference-in-differences estimator (Cengiz et al. [2019]). 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 $h = -2$

[6] We thank the authors for sharing the SBA data for our use in this paper.

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 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

[7]The $OtherDisaster$ variable also includes non-flooding PDDs for which we do not 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). The choice of $p = 5$ matches that of Roth Tran and Wilson [2023]. Estimates for our coefficient of interest are largely insensitive to the choice of p (see Appendix Figure 10).

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]).

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

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. $LocalBanking_{c,\tau-1}$ is constructed using Equation 1. $LocalBanking_{c,\tau-1}$ 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. $LocalBanking_{c,\tau-1}$ 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 $LocalBanking_{c,\tau-1}$ 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. $LocalBanking_{c,\tau-1}$ 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 using OLS.

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

The key source of deregulation is when a state first allows out-of-state banks to enter. $Interstate_{ct}$ is an indicator variable equal to one beginning in the year that a state first enacts regulation to allow out-of-state banks. $InterstateLag_{ct}$ equals zero before the year of deregulation, and then increments by one each year beginning in the year of deregulation. The lag variable captures the number of years out-of-state banks have been permitted to enter the state. We also include an indicator, $Intrastate_{ct}$, for when a state passes intrastate deregulation. Whether states are allowed to operate statewide can mechanically impact our measurement of local banking. The 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.

Equation 4 leverages the timing of state-level deregulation as plausibly exogenous variation to isolate the role that banks have in providing credit from other endogenous demand factors that influence the development of county-level banking institutions. The purpose of estimating Equation 4 is to obtain the predicted level of local banking, $Local\widehat{Banking}_{ct}$. A potential estimation concern is that $Local\widehat{Banking}_{ct}$ may be biased since we estimate the model using OLS. The parameter estimates are partially identified from improper comparisons that use already treated units as controls (e.g. Goodman-Bacon [2021]). Unfortunately, we are not able to use recent advances in the methodological literature to estimate Equation 4 (e.g. Borusyak et al. [2021]; Callaway and Sant'Anna [2021]; Dube et al. [2023]). The main constraint is that these models do not allow us to obtain time-varying fitted values of $Local\widehat{Banking}_{ct}$ for our panel years. While we are unable to definitively rule out this concern with the two-way fixed effects model, two pieces of evidence suggest that any bias is likely to be small.

First, Dube et al. [2023] reanalyze the recent study by Leblebicioglu and Weinberger [2020] using a linear projections difference-in-differences model. Leblebicioglu and Weinberger [2020] estimate a two-way fixed effects model that exploits the timing of interstate deregulation to investigate how credit affects the labor (income) share of state GDP. Dube et al. [2023] confirm the main findings in Leblebicioglu and Weinberger [2020]. Second, we compare how the estimate for the out-of-state entry dummy variable differs in our setting using the estimation approach of Callaway and Sant'Anna [2021]. The Callaway and Sant'Anna [2021] model identifies the deregulation coefficient only from comparisons between newly deregulated counties and counties that have not yet deregulated. We can only estimate the model from 1981-1992 since all states pass out-of-state entry deregulation by 1993. We estimate a deregulation point estimate of -0.057 (standard error 0.040). This estimate is slightly larger in magnitude, but statistically indistinguishable from the OLS estimate for the same time period (-0.033).[8]

[8] We estimate the model in Stata using the *csdid* package. We calculate the "simple" ATT across treatment groups and calendar time periods.

Finally, 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. There is strong support in the literature for this assumption (e.g. Morgan et al. [2004]; Jayaratne and Strahan [1996]; Bisetti et al. [2020]; Levine et al. [2020]).

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 and its effects on local banking grow over time (e.g. Oberfield et al. [2024]). 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 the 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 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.[9] 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

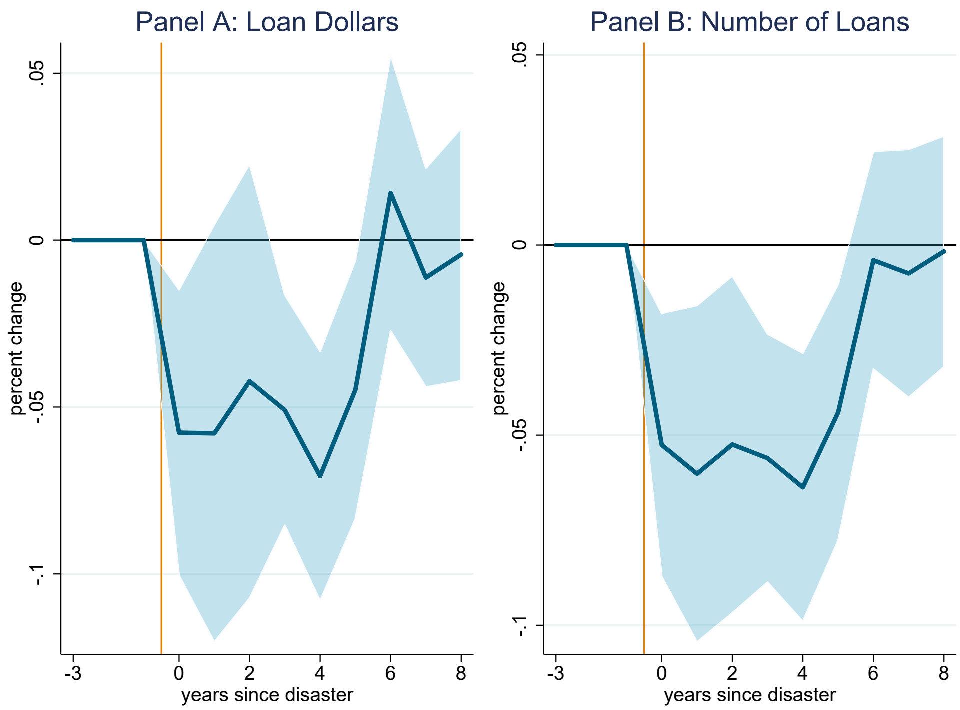
Figure 3 shows estimates of impulse response functions (IRFs) for the change in new home loans following a large disaster. We estimate the baseline model (Equation 2) that does not consider the level of local banking prior to the disaster.

The IRF for the total dollar amount of new home loans (including lines of credit) is plotted in Panel A. The figure plots β_0^h (for $h = 0$ to $h = 8$), the point estimate, as well as the 95% confidence interval, for the estimated impact of a large disaster on new lending h years after the disaster, relative to the amount of lending in the absence of a large disaster, and conditional on the other variables in Equation 2. The dependent variable in panel A (panel B) is the difference between the ln total loan amount (ln total number of loans) in year h and the ln total loan amount (ln total number of loans) in the year before the large disaster. We follow Tran and Wilson [2023] and Dube et al. [2023] and control for the lagged dependent variable in our specifications. For this reason, the plotted coefficients in the figure are normalized to zero in the years before the large disaster.

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 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

[9] There are 848 county-year observations in our sample in which the large disaster occurred eight years prior (and the calendar year is earlier than 2007).

Figure 3: **New Lending following a Large Disaster**

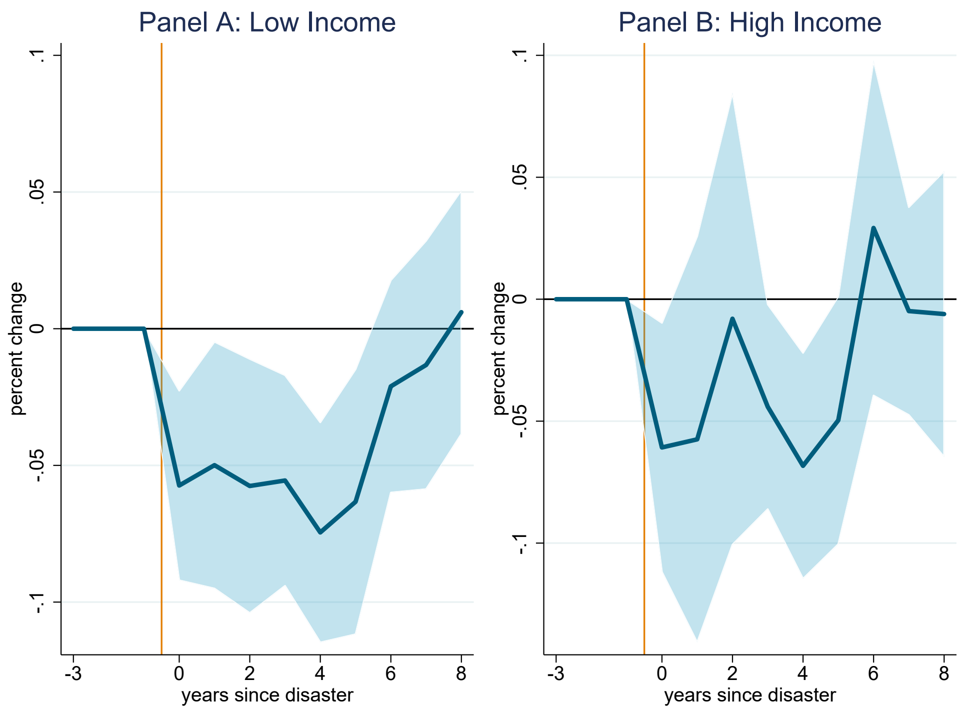


Notes: The figure plots two IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variables are ln total loan amount (panel A) and ln total number of loans (panel B). Data sources: FEMA, HMDA.

are similar to those in Panel A. The impact on the number of new loans is again largest four years after the disaster. The results are also similar for the total dollar amount of new loans *per capita* (not shown). Migration away from a disaster county is not driving the reduction in new credit following a natural 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.

Economic theory predicts that lower income individuals will be the first to lose access to credit (e.g. Townsend [1979]). Figure 4 shows how the total dollar amount of new home loans following a disaster varies for low (panel A) and high (panel B) income individuals. We classify low (high) income individuals as those in the bottom (top) tercile among loan applicants (e.g. Gelman and Park [2008]). Initially, there is a similarly sized reduction in credit for both income groups. The reduction for lower income individuals is statistically more precise and of a slightly larger magnitude across the post-disaster years. Results are similar if we use yearly national-level income thresholds from the U.S. Census Bureau to divide the income groups.[10] We view this as suggestive evidence that, overall, low income individuals may have lower access to mortgage credit following a large disaster. In the next section, we investigate how credit access varies based on the composition of the banking institutions in the county.

Figure 4: **New Lending following a Large Disaster for Low and High Income Individuals**



Notes: The figure plots two IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable is ln total loan amount, which is estimated separately for low (panel A) and high (panel B) income individuals. 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 availability 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 influence to the development of the banking institutions in a particular county.

[10]U.S. Census Bureau, Median Household Income in the United States [MEHOINUSA646N], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MEHOINUSA646N.

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. The two regulation indicator variables are statistically significant. For example, we estimate that the county local banking index is 4.3 percentage points lower (p-value < 0.01) after the passage of interstate deregulation. Recall that a lower index implies greater non-local banking. The deregulation indicator 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). The interstate lag variable is statistically significant (column (2), p-value < 0.10) when we limit the panel to start in 1990.

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

Dependent Variable: County Local Banking Index			
Panel length:	1981-2006	1990-2006	1990-2006
	(1)	(2)	(3)
Interstate Indicator	-0.043***	-0.100**	-0.099**
	(0.014)	(0.048)	(0.048)
Interstate Lag	0.005	-0.062*	-0.061
	(0.003)	(0.039)	(0.039)
Intrastate Indicator	-0.156***	-0.098***	-0.099***
	(0.011)	(0.032)	(0.031)
Disaster Indicators	X	X	X
County FE	X	X	X
Year FE	X	X	X
Drop Repeat Disaster Obs			X
R^2	0.746	0.805	0.805
Observations	74,411	51,356	49,722

Data Sources: FDIC, FEMA, Morgan et al. [2004], Bisetti et al. [2020]. Significance level: *** 1%, ** 5%, * 10%.

Table 3 compares counties with a high level of non-local banking to counties with a high level of local banking along six socioeconomic variables. We use socioeconomic information from the 1980 US Decennial Census, as this is the last US Census before the interstate deregulation that began in the 1980s. We split counties based on whether they are in the top or bottom tercile of the 1995 banking index (panel A) and instrumented banking index (panel B). We use the index from 1995 as this marks the end of the interstate deregulation wave. The analysis is similar if we use the banking index from later years.

Table 3 panel A matches Figure 1 panel A and divides counties by the actual banking index. Counties with greater non-local banking are characterized by higher home values, higher income residents, lower poverty rates, and higher employment. These counties are also more urban and have a higher share of residents who graduated from college. We can statistically reject at the 1% significance level that counties in the 1st and 3rd terciles of the banking index have the same values for each of the socioeconomic variables. The probability values for all six t-tests are less than 0.005.

Table 3: **Comparison of County Socioeconomic Characteristics by the Level of the Local Banking Index**

	Median Home Value	Median HH Income	Poverty Rate (%)	Employment (%)	College Degree (%)	Urban (%)
A. Banking Index						
High level of non-local banking	39,378	14,791	0.15	0.54	0.13	0.40
High level of local banking	29,304	13,101	0.18	0.52	0.10	0.26
Difference	10,074	1,690	-0.03	0.02	0.03	0.14
p-value	0.000	0.000	0.002	0.004	0.000	0.000
B. Instrumented Banking Index						
High level of non-local banking	34,769	13,914	0.16	0.53	0.11	0.34
High level of local banking	32,402	13,500	0.16	0.54	0.12	0.31
Difference	2,367	414	0.00	-0.01	-0.01	0.03
p-value	0.349	0.522	0.924	0.530	0.262	0.346

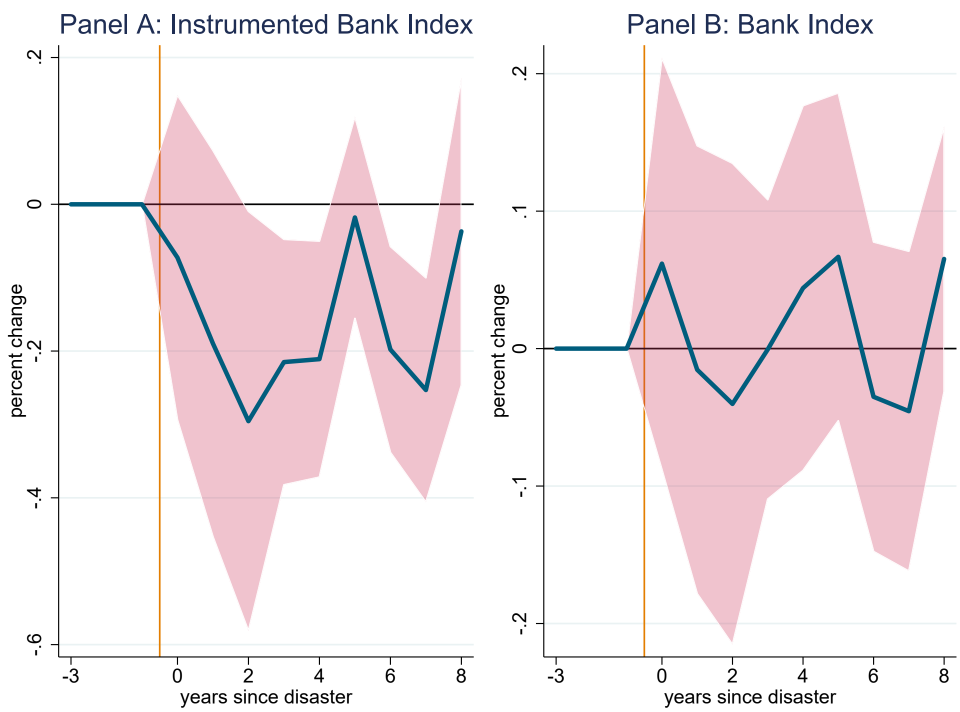
Notes: Counties with a high level of non-local (local) banking have a banking index in the 1st (3rd) tercile. The table includes probability values from 12 separate t-tests of the hypothesis that the means for the 1st and 3rd tercile groups in each panel-column are equivalent. We run the regression using OLS and cluster the standard errors by state. Data sources: FEMA, HMDA, US Census.

Panel B of the table provides the same comparison for counties in the 1st and 3rd terciles using the instrumented banking index. The 1st and the 3rd terciles of the instrumented banking index have similar characteristics. The difference between the means is an order of magnitude smaller for four of the six socioeconomic variables, as compared to panel A. None are statistically significantly different from zero at the 5% significance level. Overall, Table 3 shows the importance of using the instrumented banking index to isolate the role of local banks from the endogenous economic conditions that influence the composition of banking in a region.

Figure 5 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 0.12 and 0.65, respectively. The estimated difference in new lending in counties at the first and third banking index quartiles in the four years post-disaster is approximately: $(-0.25 * 0.12) - (-0.25 * 0.65) = 0.13$. Counties with a greater share of local banking are estimated to have 13 percentage points less lending, as compared to counties with a lower share of local banking.[11]

Figure 5: **New Home Loans after a Large Disaster by Level of the Local Banking Index**



Notes: 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], Bisetti et al. [2020].

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 from zero.

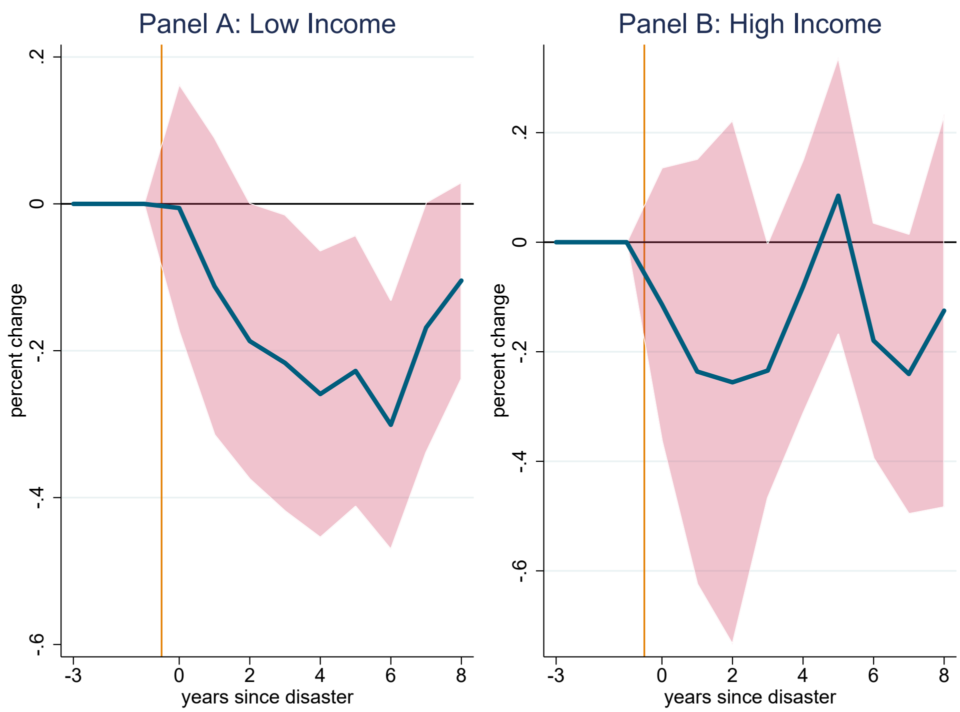
There are numerous anecdotes of local banks providing needed credit for lower income disaster victims in the community in which they operate. Examples include in New Orleans after Hurricane

[11] The estimated *overall* lending effect from this model is calculated as: $\hat{\beta^h_\tau} + \hat{\delta^h} * \widehat{LocalBanking}_{c,\tau-1}$. The estimated coefficients for a (non-interacted) large disaster, $\hat{\beta^h_\tau}$, are positive, but not statistically different from zero for the first five post-disaster years.

Katrina and in rural Mississippi following recent flooding and tornadoes (Burnett [2008]; Anderson [2023]). Figure 6 tests whether a higher concentration of local banking in a county may benefit lower income individuals following a large disaster. We do not find that these anecdotes generalize.

Figure 6 shows the interaction coefficient of interest from estimating the change in loan dollars using Equation 3 when we instrument for local banking. An increase in the concentration of local banking at the time of the disaster leads to a reduction in credit for both income groups. The reduction for low income individuals is statistically different from zero for most of the post-disaster years, and slightly larger in magnitude than the average (all incomes) estimate in Figure 5 panel A. The reduction is less precisely estimated for the high income group.

Figure 6: **New Home Loans after a Large Disaster by Level of the Local Banking Index for Low and High Income Individuals**



Notes: The figure plots the local banking index by large disaster (interaction variable) point estimates and 95% confidence intervals from estimating Equation 3. The dependent variables is ln total loan amount, which is estimated separately for low (panel A) and high (panel B) income individuals. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

4.3 Discussion

We find a reduction in new credit following a natural disaster. Regions with more local banking at the time of the disaster have larger drops in new lending post-disaster. This is consistent with the *capacity* prediction dominating the *incentive* and *information* predictions in our theoretical framework. Low income individuals living in regions with a greater share of local banking are the group with the largest drop in new credit. We mostly interpret these findings as private lenders pulling back the amount of new lending following a natural disaster.

4.3.1 Bank Lending and Direct Federal Disaster Assistance

After large disasters, residents in disaster counties may use federal disaster assistance to substitute for private sector lending following a natural disaster. Small Business Association (SBA) household disaster loans and cash grants through FEMA's Individual Assistance program are the two main sources of direct federal disaster assistance. Residents impacted by a natural disaster can apply for SBA household disaster loans to repair or replace homes, autos, and the contents of the home. Typically, an impacted resident must first apply for a SBA loan before being eligible for cash grants via the Individual Assistance program.[12]

Appendix Table 6 shows the mean amount of new private sector lending, SBA disaster loans, and FEMA Individual Assistance in disaster counties in the year of a disaster. The table underscores the importance of private sector lending following a natural disaster. Largely missing from the existing literature is a comparison of the relative sizes of private sector lending and direct federal disaster assistance. The dollar amount of new home loans is two orders of magnitude larger than the sum of SBA disaster home loans and Individual Assistance cash grants.[13] The relative size difference suggests that, at most, only a small fraction of private lending could be crowded out by direct federal disaster assistance. Collier et al. [2024] find no evidence of private lending being displaced by SBA household disaster loans, and actually find that receipt of a SBA loan causes an increase in auto borrowing. Data limitations prevent us from testing how much federal disaster assistance displaces the overall amount of private lending.

We are able to test whether there is a difference in direct federal disaster assistance at the

[12] See Collier et al. [2021], Begley et al. [2024], and Collier and Ellis [2024] for detailed discussions of the SBA disaster loan program, the cost of borrowing, and estimates on loan access and take-up. Gallagher et al. [2023] examine the Individual Assistance program and show that disaster victims appear to use Individual Assistance grants to substitute for credit card debt. Deryugina [2017] shows that non-disaster federal transfers to residents in disaster counties following a hurricane are substantial. The transfers persist for a number of years and exceed the amount of direct federal disaster assistance.

[13] Hong et al. [2020] and Ouazad and Kahn [2022] also highlight the size and importance of private sector lending following a natural disaster.

time of a disaster based on the amount of local banking in the county. The first four columns of Table 4 show the mean amount of SBA disaster loans and FEMA Individual Assistance distributed to a county in the year of a disaster, by the quartile of a county's predicted local banking index. The means are estimated from a regression model that controls for year and county fixed effects. The standard errors (in parentheses) are clustered at the state-by-year level. The difference in the means across the four columns is economically small for both types of disaster assistance.

The two rightmost columns in Table 4 test whether there is a difference in the mean amount of direct disaster assistance in the year of a disaster based on the level of local banking. One might hypothesize that SBA disaster loans and Individual Assistance grants could crowd out private lending. Greater direct federal assistance in locations with more local banking could partially explain why post-disaster lending by private lenders decreases more in regions with greater local banking. However, we find no evidence that there are differing levels of direct federal disaster assistance in counties with lower versus higher levels of local banking. We fail to reject the null hypothesis that the means are equivalent (probability values ranging from 0.776 to 0.905).

Table 4: **Direct Federal Disaster Assistance to Disaster Counties in the Year of Disaster by Local Banking Quartile**

	Predicted Local Banking Index Quartile				F-Test Equivalence of Means	
	Q1	Q2	Q3	Q4	Q1 = Q4	(Q1+Q2) = (Q3+Q4)
SBA Disaster Loans	-284	-19,742	1,378	13,547	0.905	0.776
	(107,110)	(34,837)	(31,117)	(42,980)		
Individual Assistance	169,926	-235,982	-69,645	69,402	0.778	0.876
	(349,030)	(174,573)	(145,464)	(67,347)		

Notes: The table shows the mean amount (standard errors in parentheses) of SBA disaster loans and FEMA Individual Assistance distributed to a county in a year of a disaster (2014$), by the quartile of a county's predicted local banking index. The means are estimated from a regression model that controls for year and county fixed effects. Standard errors are clustered at the state-by-year level. Quartile one (Q1) of the index are counties with the least amount of local banking at the time of the disaster, while quartile four (Q4) are counties with the most amount of local banking. Probability values for the equivalence of means from a F-test are displayed in the two rightmost columns. Data Sources: Bisetti et al. [2020], FDIC, FEMA, Morgan et al. [2004], SBA.

Appendix Figure 11 shows the impact of a large disaster on direct federal assistance using our event study model. The main challenge in estimating the *change* in the amount of SBA disaster loans and Individual Assistance using Equation 3 is that, by definition, there is no federal assistance distributed in most county-years. Individual Assistance is only allocated after *some* Presidential Disaster Declarations. SBA disaster loans are more common, but still non-zero in only 12% of the county-years in our main estimation panel. Still, the estimated results in Appendix Figure 11 match those in Table 4. There is no statistically significant difference in the amount of SBA loans or Individual Assistance grants in the year of the disaster based on the level of local banking in the county.

4.3.2 Local Banking and Loan Performance

The soft information collected by local lenders, together with a detailed understanding of the local market, may allow local lenders to better assess risk relative to national lenders (e.g. Berger et al. [2005]). The overall level of lending decreases in regions with greater local banking. However, more accurate risk assessment by local lenders may result in better loan performance among the pool of loans that they originate. Improved loan performance could lead to greater local economic recovery, for example, by leading to a more stable population. Fewer delinquencies and foreclosures may also reflect a more efficient allocation of credit and contribute to economic growth (Barlevy [2003], Davis and Haltiwanger [1990]).

We investigate loan performance using loan-level delinquency information from the Federal Reserve Bank of New York Equifax Consumer Credit Panel (Equifax CCP) (e.g. Lee and van der Klaauw [2010]; Gallagher and Hartley [2017]). Equifax is a large consumer credit repository. The panel is constructed using an anonymized 5% sample of the US population based on the last two digits of an individual's Social Security number. Presence in the panel is also conditional on having an active credit file. The Equifax CCP contains credit account information by type of account. The information for home loans includes loan-level initiation dates, and delinquency flags for delinquency lengths of 30, 60, 90, and 120 days. We aggregate information on 30 and 90 day delinquencies to the county level and create delinquency rate variables. Our baseline delinquency rate variables measure the fraction of home loans initiated in a county in a particular year that are flagged as being 30 (or 90) days delinquent sometime over the first five years of the loan. A limitation of the the Equifax CCP data in our setting is that the panel begins in 1999, and thus only covers the second half of our main sample.

Figure 7 shows results using our event study models for the 1999-2007 sub-sample covered by the Equifax CCP. Panel A estimates how the 30 day delinquency rate for new home loans changes following a large disaster. Overall, there is approximately a 0.55 percentage point (4%) increase in the five year delinquency rate for new loans initiated in the first post-disaster year.[14] There is no evidence that the delinquency rate differs based on the level of (predicted) local banking. None of the coefficients in the right hand side figure in Panel A are statistically different from zero. Panel B displays similar results for the 90 day delinquency rate. The point estimate for the change in the overall delinquency rate for new loans initiated in the first post-disaster year is approximately 0.4 percentage point (6%). The confidence interval narrowly contains zero. Again, there is no evidence that the change in the 90 day delinquency rate differs by the level of local banking in the county.

5 The Impact of Large Disasters on Local Economic Outcomes

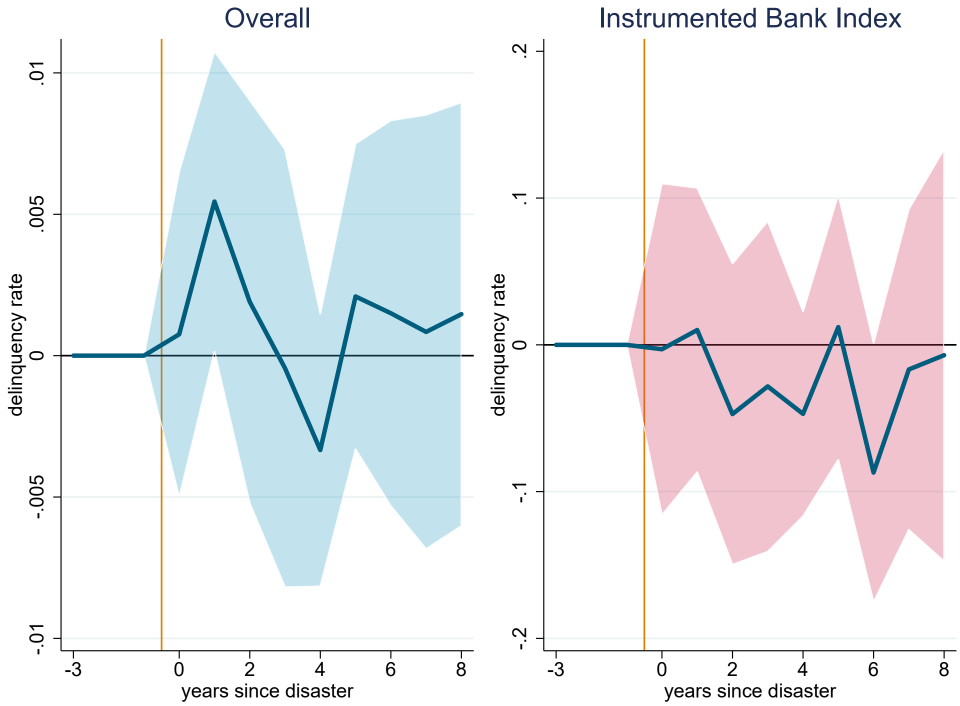
We estimate the impact of a large natural disaster on the local economy in Figure 8 panel A. Wages and employment increase in disaster counties by around 1%. These estimates are broadly consistent with Roth Tran and Wilson [2023], who find positive employment and wage effects of a similar magnitude. 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 Roth Tran and Wilson [2023] find no impact on future population growth following natural disasters in the US during the late 20th century.

Figure 8 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 the instrumented banking index) from Equation 3. 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.

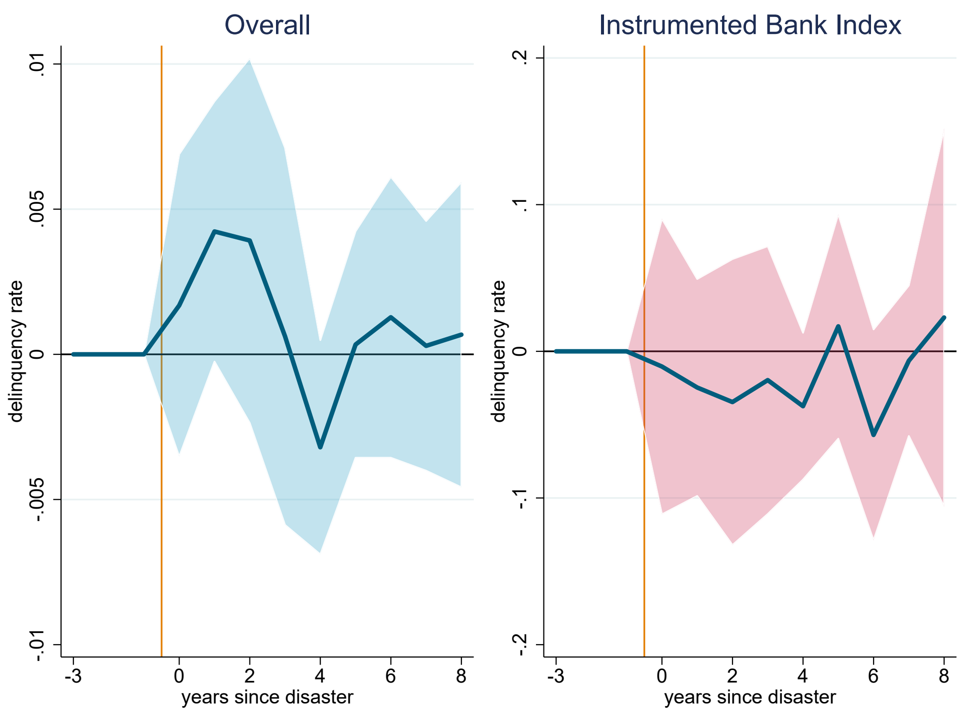
[14]The percent increase is calculated relative to the mean in Appendix Table 6.

Figure 7: **New Loan Delinquency for Home Loans Issued after a Large Disaster**

Panel A: 30 Day Delinquency



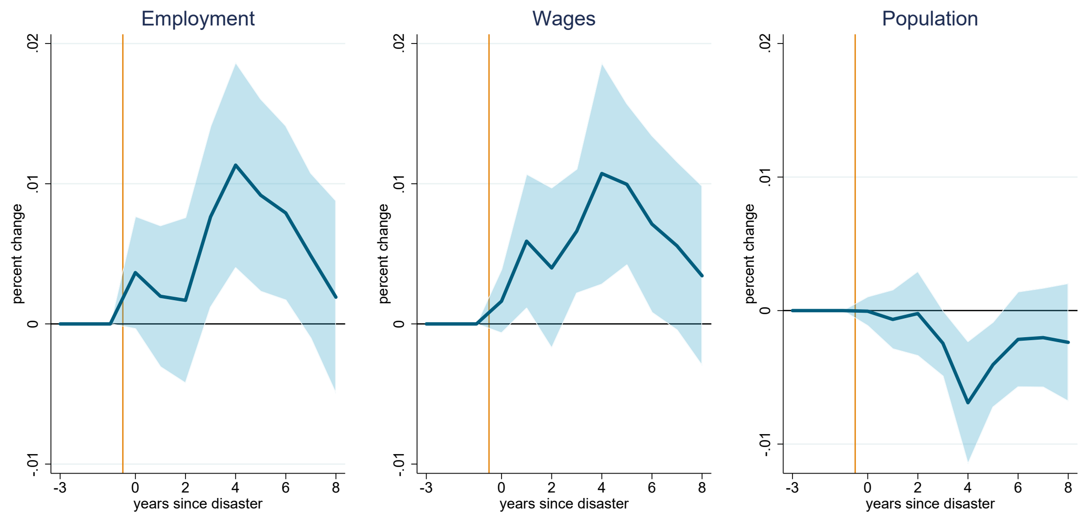
Panel B: 90 Day Delinquency



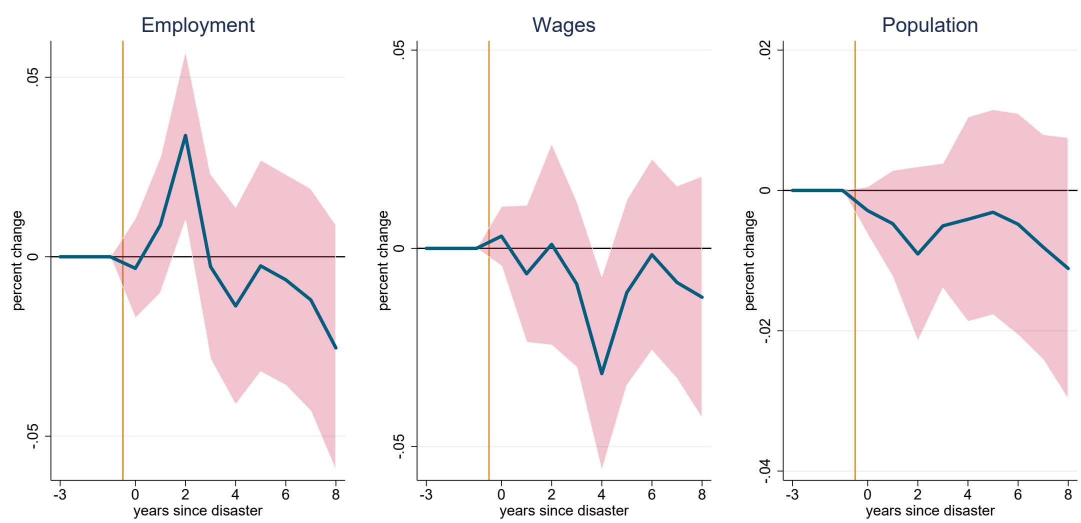
Notes: The dependent variable is the share of new loans issued in a particular year that are classified as being 30 days delinquent (Panel A) or 90 days delinquent (Panel B) at some point in the first five years of the loan. The left hand side of the figure plots point estimates and 95% confidence intervals for the overall impact on delinquency rates from estimating Equation 2. The right hand side of Panels A and B plots the predicted local banking index by large disaster (interaction variable) point estimates and 95% confidence intervals from estimating Equation 3. Data sources: Equifax CCP, FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 8: **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 that differ only by the dependent variable: ln adult employment rate, ln wages per capita, and ln 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.

6 Conclusion

We show that new home lending 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 using verified damage to public infrastructure. Defining a large natural disaster in this way screens out counties with little damage that were swept up in a Presidential Disaster Declaration and circumvents the empirical challenges of using weather damage information from SHELDUS, a commonly used database.

The reduction in lending is greater in counties with a higher share of local banking at the time of the large disaster. We define local banking based on the concentration of FDIC bank deposits. 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 show that large and statistically significant differences in the levels of county-level socioeconomic variables disappear after instrumenting. There is suggestive evidence that the reduction in new credit following a large disaster is greatest for low-income individuals. The reduction in credit is consistent with moral hazard considerations limiting the supply of credit. We show that direct federal disaster assistance cannot account for the overall drop in new credit, and differing levels of direct federal assistance cannot explain why regions with greater local banking at the time of the disaster experience a larger drop in lending.

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%. At the same time, there is some evidence for a very small and temporary decrease of 0.25%-0.5% in the population. 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. However, there also appears to be an immediate boost in employment post-disaster in these same counties. One possibility is that the modest reduction in credit in regions with more local banking at the time of a natural disaster is too limited to dramatically impact countywide economic outcomes. Another possibility is that there is unexplained heterogeneity in the impact of reduced credit on a region's post-disaster economic recovery. We plan to explore how the concentration of local banking affects within-county post-disaster economic performance in future work.

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.

Sarah Abraham and Liyang Sun. Estimating dynamic treatment effects in event studies with heterogenous treatment effects. *The Journal of Econometrics*, Forthcoming.

Federal Emergency Management Agency. Declared disasters. Technical report, 2019. URL https://www.fema.gov/disasters/disaster-declarations.

Andy Anderson. Bank of anguilla's role in the local economic recovery from recent natural disasters. Technical report, Prepared remarks at the 2023 Federal Reserve Community Banking Research Conference, October 2023.

Gadi Barlevy. Credit market frictions and the allocation of resources over the business cycle. *Journal of monetary Economics*, 50(8):1795–1818, 2003.

Taylor A. Begley, Umit G. Gurun, Amiyatosh Purnanandam, and Daniel Weagley. Disaster lending: "fair" prices but "unfair" access. *Management Science*, Online, 2024.

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.

Allen N. Berger, Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein. Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76:237–269, 2005.

Allen N. Berger, Christa H.S. Bouwman, and Dasol Kim. Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance. *The Review of Financial Studies*, 30, 2017.

Stephen B Billings, Emily A Gallagher, and Lowell Ricketts. Let the rich be flooded: the distribution of financial aid and distress after hurricane harvey. *Journal of Financial Economics*, 146(2):797–819, 2022.

Emilio Bisetti, Stephen A. Karolyi, and Stefan Lewellen. The blessing and curse of deregulation. *SSRN Working Paper*, November 2020.

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.

John Burnett. Trust guides bank's new orleans rebuilding effort. *NPR*, April 2008. URL https://www.npr.org/templates/story/story.php?storyId=89532824.

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 and Pedro H.C. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225, 2021.

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.

Doruk Cengiz, Arindrajit Dube, Attila Lindner, and Ben Zipperer. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454, 2019.

Matthieu Chavaz. Dis-integrating credit markets: diversification, securitization, and lending in a recovery. *Bank of England Staff Working Paper*, (617), September 2016.

Benjamin Collier and Cameron Ellis. A demand curve for disaster recovery loans. *Econometrica*, 92(3): 713–748, 2024.

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.

Benjamin L. Collier, Cameron M. Ellis, and Benjamin J. Keys. The cost of consumer collateral: Evidence from bunching. *NBER Working Paper*, (29527), 2021.

Benjamin L. Collier, Daniel A. Hartley, Benjamin J. Keys, and Xian Ng. Credit when you need it. *Working Paper*, 2024.

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.

Steven J Davis and John Haltiwanger. Gross job creation and destruction: Microeconomic evidence and macroeconomic implications. *NBER macroeconomics annual*, 5:123–168, 1990.

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 study. 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://justinpgallagher.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.

Justin Gallagher, Daniel Hartley, and Shawn Rohlin. Weathering an unexpected financial shock: The role of federal disaster assistance on household finance and business survival. *Journal of the Association of Environmental and Resource Economists*, 10(2), March 2023.

Andrew Gelman and David K. Park. Splitting a predictor at the upper quarter or third and the lower quarter or third. *The American Statistician*, 62(4), November 2008.

Edward Glaeser. Cities, productivity, and quality of life. *Science*, 333:592–594, July 2011.

Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, March 2021.

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.

Harrison Hong, G. Andrew Karolyi, and Jose A. Scheinkman. Climate finance. *The Review of Financial Studies*, 33(3):1011–1023, 2020.

Solomon Hsiang and Amir S. Jina. The causal effect of environmental catastrphe 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.

Ash Leblebicioglu and Ariel Weinberger. Credit and the labour share: Evidence from us states. *The Economic Journal*, 130(630), 2020.

Donghoon Lee and Wilbert van der Klaauw. An introduction to the frbny consumer credit panel. *Technical Report 479, Federal Reserve Bank of New York*, November 2010.

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 riegle-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.

Ezra Oberfield, Esteban Rossi-Hansberg, Nicholas Trachter, and Derek T. Wenning. Banks in space. *NBER Working Paper*, (32256), 2024.

Amine Ouazad and Matthew E. Kahn. Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters. *The Review of Financial Studies*, 35(8):3617–3665, 2022.

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 heterogeneou treatment effects. *Journal of Econometrics*, 2021.

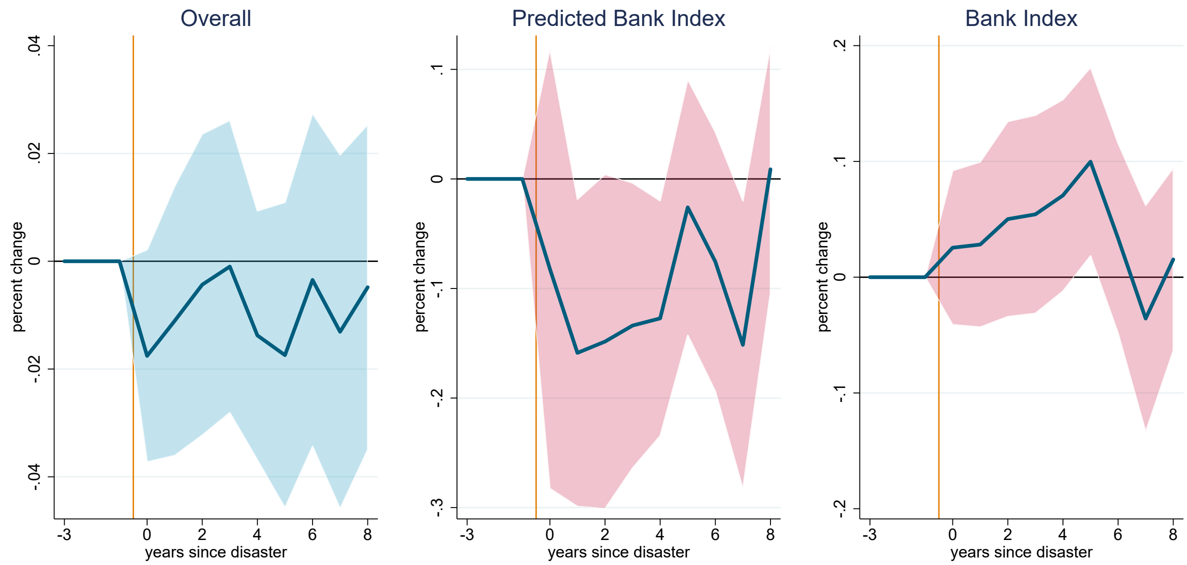
Robert Townsend. Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory*, 21:265–93, 1979.

Brigitte Roth Tran and Daniel J. Wilson. The local impact of natural disasters. *Federal Reserve Bank of San Francisco Working Paper*, February 2023.

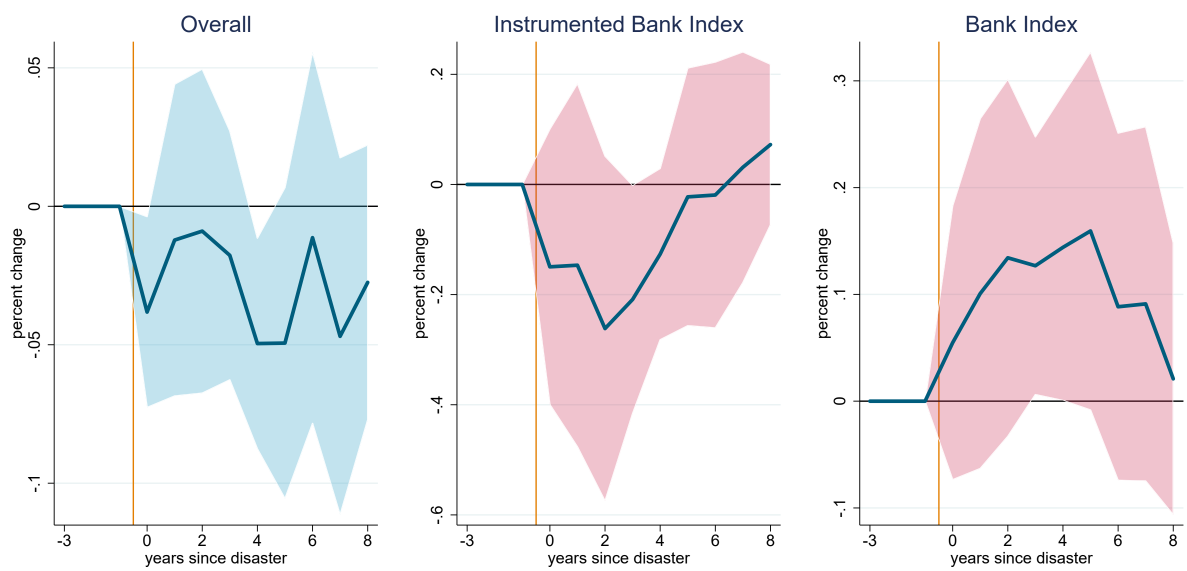
8 Appendix

Figure 9: **New Lending following a Large Disaster - Robustness to the Definition of a Large Disaster**

Panel A: Exceeding the 50th County Cost Percentile



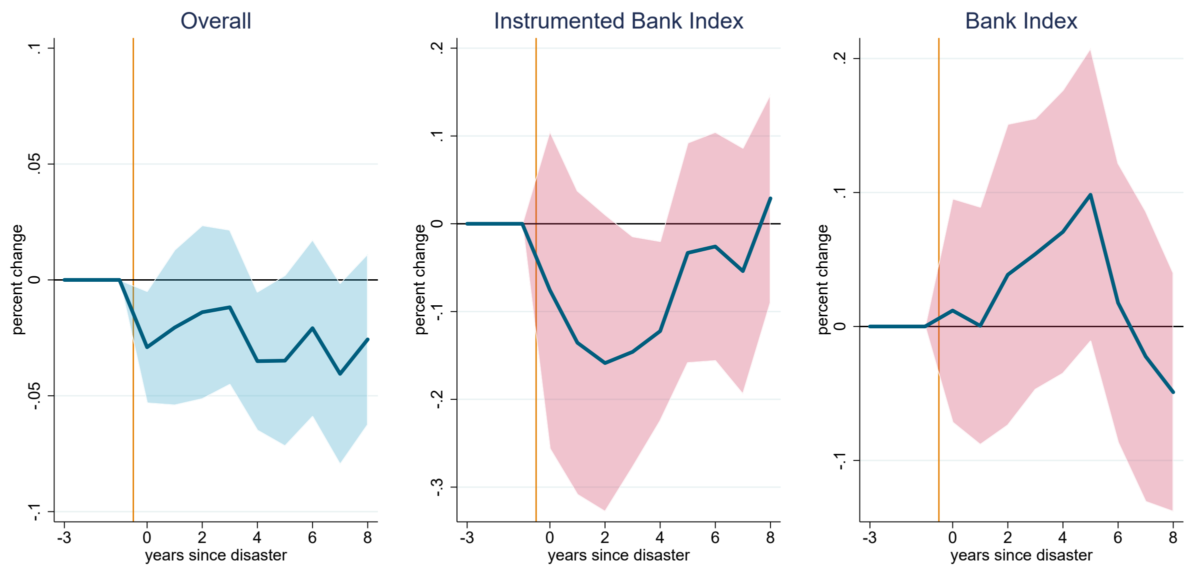
Panel B: Exceeding the 90th County Cost Percentile



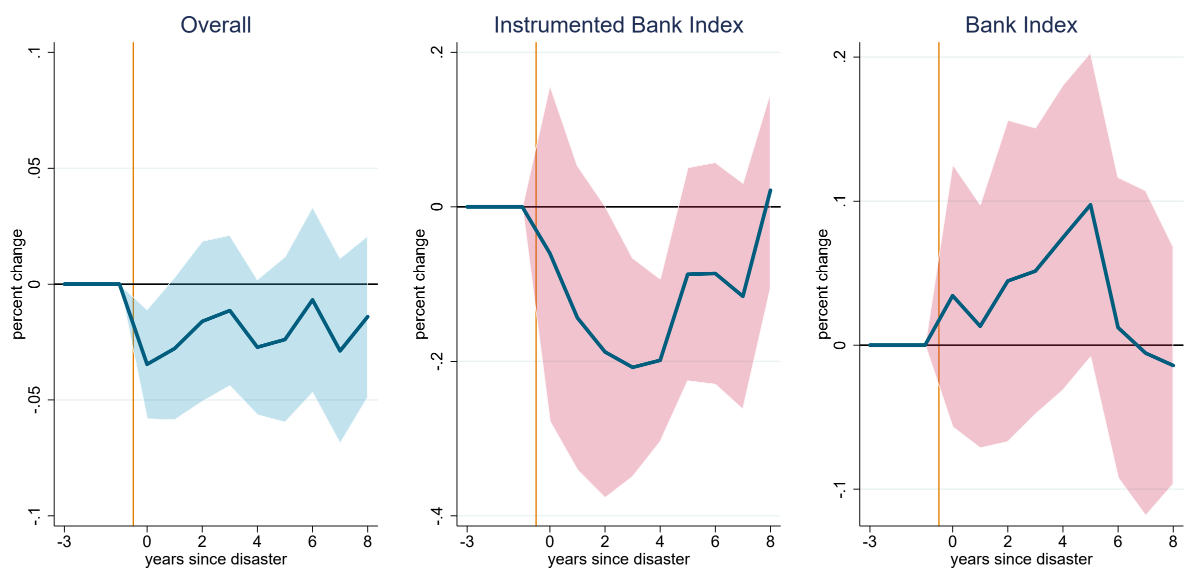
The figure plots IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable is ln total loan amount. Our baseline definition of a large disaster in the paper is one that exceeds the 75th percentile in county-level cost. By contrast, Panel A of this figure defines a large disaster as exceeding the 50th percentile, while Panel B defines a large disaster as exceeding the 90th percentile. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 10: **New Lending following a Large Disaster - Robustness to the Assumption over when the Impact of a Large Disaster Stabilizes**

Panel A: Assume Disaster Impact Stabilizes Immediately



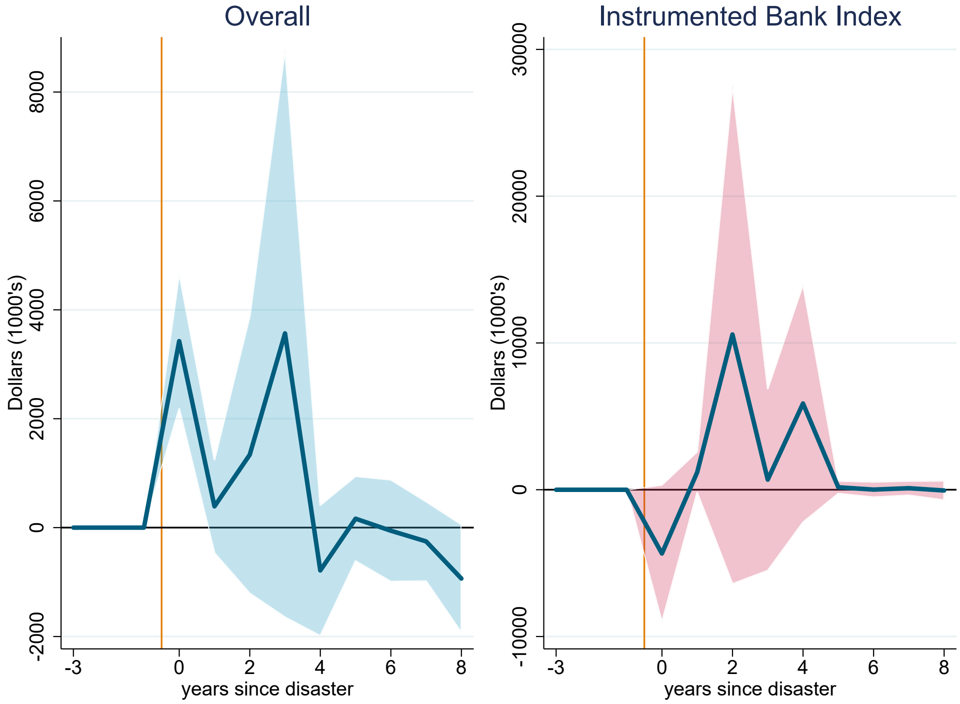
Panel B: Assume Disaster Impact Stabilizes after 10 Years



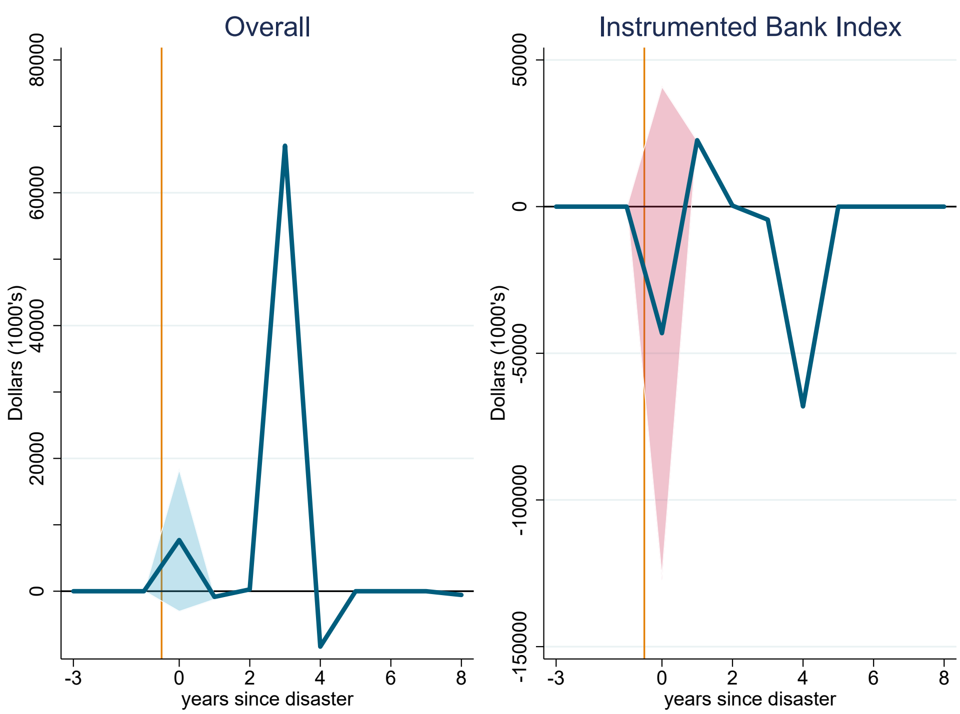
The figure plots IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable is ln total loan amount. Our baseline model assumes that the impact of a large natural disaster stabilizes after five years. By contrast, Panel A assumes that the impact stabilizes immediately (zero years), while Panel B assumes that the impact stabilizes after ten years. a large disaster as exceeding the 90th percentile. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 11: **Direct Federal Disaster Assistance following a Large Disaster**

Panel A: SBA Disaster Home Loans



Panel B: Individual Assistance Grants



The figure plots IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable in Panel A is the total amount of new SBA disaster home loans. The dependent variable in Panel B is the total amount of Individual Assistance. Both dependent variables are measured in 1000's of 2014$. There are very few county-years with non-zero Individual Assistance in the 8 years following a large disaster (and not enough to calculate standard errors and confidence intervals). We display the same event study time period so as to be consistent with our other results. Data sources: FDIC, FEMA, SBA, Morgan et al. [2004], Bisetti et al. [2020].

Table 5: **List of Data Sources**

Data	Time Span	Geography	Source
Bank deposits	1981-2007	county	Summary of Deposits from Federal Deposit Insurance Corporation (FDIC).
			Accessed via FDIC website.
Bank deregulation	1970-2007	state	Morgan, Rime, and Strahan (2004). Bisetti, Karolyi, and Lewellen (2020).
Business loans	1997-2007	county	Aggregate and Disclosure Flat Files.
			Accessed via Federal Financial Institutions Examination Council (FFIEC) website.
Disaster Assistance	1990-2007	county	Individual Assistance via Freedom of Information Act (FOIA) request.
Disaster loans	2001-2007	county	Small Business Administration (SBA) disaster loans accessed via the SBA website.
	1991-2007	county	SBA disaster loans. Compiled via a Freedom of Information Act (FOIA) request by
			Begley, Gurun, Purnanandam, and Weagley (2024). Shared by Taylor Begley.
Employment	1980-2007	county	US Census Bureau. Accessed posted data files for Deryugina (2017).
		county	County Business Patterns employment by 2-digit industry code.
			Panel with harmonized 2012 industry codes: https://fpeckert.me/cbp
Home loans	1990-2007	county	Home Mortgage Disclosure Act (HMDA).
Loan delinquency	1999-2007	county	Federal Reserve Bank of New York Consumer Credit Panel / Equifax (CCP).
Natural disasters	1981-2007	county	Presidential Disaster Declaration location, type, and date.
			Accessed via Federal Emergency Management Administration (FEMA) website.
Natural disaster cost	1981-2000 (approx.)	state	Public Assistance, FEMA website.
	2001-2007 (approx.)	county	Public Assistance, FEMA website.
	1990-2007	county	Public Assistance, FOIA request.
Population	1980-2007	county	National Bureau of Economic Analysis (NBER). Accessed via NBER website.
Wages	1980-2007	county	US Bureau of Economic Analysis. Accessed posted data files for Deryugina (2017).

Table 6: **Summary Statistics**

	1990		2007		1990-2007	
	Mean	Median	Mean	Median	Mean	Median
I. Loan Information						
Business Loans[1]						
Number	789	169	4,291	748	2,215	419
Amount ($1,000)	72,637	11,431	118,336	17,836	95,764	16,079
Home Loans						
Number	1,100	45	3,298	664	3,283	394
Amount ($1,000)	206,376	3,598	749,050	76,898	616,578	35,077
Amount ($1,000), cond'l disaster	287,137	2,930	1,122,853	51,740	753,117	46,286
SBA Disaster Home Loans[2]						
Amount ($1,000)	79	0	149	0	447	0
Amount ($1,000), cond'l disaster & > 0	3,152	38	1,543	333	3,648	160
Home Loan Delinquency Rate[3]						
30 days del. & within 5 yrs of loan	0.15	0.14	0.18	0.18	0.14	0.13
90 days del. & within 5 yrs of loan	0.07	0.06	0.12	0.11	0.07	0.06
Individual (Disaster) Assistance						
Amount ($1,000), cond'l disaster & > 0	306	60	1,168	319	4,167	155
II. Economic Information						
Local Banking Index	0.41	0.34	0.33	0.29	0.39	0.35
Employment Rate	0.32	0.30	0.35	0.33	0.35	0.32
Population	79,749	22,335	96,410	25,605	87,872	24,190
Ln Wage Per Capita	9.24	9.24	9.46	9.46	9.35	9.34
III. Disaster Information[4]						
County Disasters	577	-	770	-	754	737
County Flooding Disasters	519	-	698	-	624	558
Cost ($1,000), cond'l disaster and > 0	606	342	1,629	398	4,596	304

The table shows summary statistics for the natural disaster data and the dependent variables used in the analysis. Each row displays the mean and median for the first year of the panel (1990), the last year in the panel (2007), and across the entire panel (1990-2007). The means and medians calculated in the 1990 columns for the following variables are for the first year of data availability (see Appendix Table 5): [1]business loan data (1997), [2]SBA disaster home loans (1991), [3]delinquency rate (1999). [4]The table displays the number (count) of county-level disasters for 1990 and 2007 (not the mean number). The cost information is county-level Public Assistance and not available for all disasters. All dollars in 2014 $. The statistics that are conditional on a disaster are conditional for any disaster (and not only large disasters). Sources: Bisetti et al. [2020], Equifax CCP, FDIC, FEMA, FFIEC, HMDA, Morgan et al. [2004], NBER, SBA, US Census Bureau.