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Natural Disasters, Local Bank Market Share, and Economic Recovery

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Abstract

The frequency and severity of natural disasters have increased over the past few decades. Credit from private banking sources is a critical source of funding following a natural disaster. New post-disaster mortgage and home loan credit is two orders of magnitude larger than the level of federal disaster assistance provided to disaster-affected residents. 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 a natural disaster. We isolate the causal role that banking institutions have on the supply of credit by instrumenting for the composition of local and national banking institutions in a region at the time of a natural disaster using state-level bank deregulation. Overall, we find that there is less new credit in disaster regions for about five years following a natural disaster. The reduction in credit is greater in regions with a higher concentration of local banking. Regions with a higher concentration of local banking are also characterized by somewhat weaker redevelopment as measured by wage and population growth.

JEL Codes: G21, O16, Q54, R11

Keywords: natural disasters, community banks, bank credit, economic recovery

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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 through 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 following 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 contrast, 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]).

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, and in turn, 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). Credit from private banking sources is a critical source of funding following a disaster. Our analysis shows that, after a disaster, 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 is needed 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]). 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 important (e.g. Roth Tran and Wilson [2024]).

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 (PDDs), where each declaration designates the counties impacted by a natural disaster. We estimate a county-level model because we are interested in how bank credit impacts regional recovery and redevelopment, and because PDDs are declared at the county level and key economic data are available at the county level.

We proxy for disaster damage with a measure of federal disaster assistance to repair public

infrastructure. 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. We aggregate these lender-specific data to the county-level.² 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 (LPDiD) (e.g. Dube et al. [2023]; Roth Tran and Wilson [2024]). We use FDIC bank deposit information to construct a measure of local banking for each county during each year based on the location of bank deposits.

A key empirical challenge is that the development of local banking institutions is endogenous to local economic conditions. We are interested in isolating the role that local banking institutions have on credit provision and local economic development following a natural disaster. The exact location and timing of a natural disaster is (arguably) exogenous, after controlling for local disaster risk and time trends. However, the types of local banking institutions in a region at the time of a disaster are endogenous and depend on many factors, including: household wealth and income, the strength of the local economy, and the demographics of the residents.³

A simple example helps to highlight this identification concern. Suppose that there are two counties, county A (Arlington, VA) and county B (Breathitt, KY). Each county is hit by a natural disaster in the same year. The population of county A has a high level of wealth and is mostly served by national banking institutions. The population of county B has a low level of wealth and is primarily served by local banking institutions.⁴ If we find that there is greater post-disaster bank

¹We do not use disaster damage reported in SHELDUS, as is common among researchers studying natural disasters. Gallagher [2023] shows that SHELDUS (SHELDUS [2025]) 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.

²As a robustness check, we also estimate a bank-level model which shows similar results to our main credit allocation findings from the preferred county-level model.

³We document these factors in Table 3.

⁴Arlington county and Breathitt county are located in neighboring states. Both counties experienced a Presidential Disaster Declaration disaster in 1996. At the time of the natural disaster, Arlington had a high share of banking from national lenders, while Breathitt had a high share of banking from local lenders (author calculation, see Equation 1). At the same time, Arlington had one of the lowest county-level poverty rates and Breathitt one of the highest

credit provided in county A, is this because national lenders are more likely to lend to a disaster region, or is it because the existing wealth of the residents make lending to these residents more attractive? Similarly, if the economy of county A recovers more quickly following the disaster, is this because of the increased lending, or because the higher wealth of the local population make this population more resilient to the natural disaster?⁵

In order to isolate the role that the type of banking institution has on credit provision and local economic development following a disaster, we use an instrumental variables model. We instrument for the local bank market share using the timing of state-level banking deregulation (Morgan et al. [2004]; Bisetti et al. [2020]). 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 have 3 main findings. First, 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 models that predict reductions in credit when there is a capital shock to a financial intermediary in settings with asymmetric information (e.g. Townsend [1979]; Holmstrom and Tirole [1997]).

Second, we estimate that there is 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. 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.

Third, 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 county-level poverty rates in the country (US Census [2000]).

⁵In principle, the causal effect that the composition of banking institutions have on the level of post-disaster credit can be estimated in an OLS regression, provided that all pre-existing factors that affect credit supply decisions for all lenders are known, measured, and controlled for in the model. In practice, it is likely that there are factors that affect credit supply decisions by banks that researchers can not observe and control for.

six years following a large disaster. There is some evidence for a small and temporary reduction in population. Wage increases 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.

We contribute to the literature on 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 [2024]) economies. One question that has largely been ignored in this literature is the role that local banking institutions play in post-disaster recovery (e.g. Cortes [2014]; Collier and Babich [2019]). 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.

We also add to the literature that examines locally focused private lending institutions and the level of post-disaster credit to a region. Morse [2011] and Berg and Schrader [2012] document the increased demand for private credit following a natural disaster. Morse [2011] finds that access to payday lenders, who provide high-interest short-term loans for low-credit individuals, leads to a decrease in home foreclosures in California following a natural disaster. Berg and Schrader [2012] find that microfinance institutions in Ecuador are more-likely to provide credit following a natural disaster if they have a pre-existing relationship with the applicant. Two working papers find that local lenders increase credit following a disaster (Cortes [2014]; Chavaz [2016]). Cortes [2014] examines very local lenders with at least 65% of deposits in a single county or MSA and concludes that these lenders increase post-disaster employment growth for young and small firms in disaster regions. Chavaz [2016] finds that local banks provide more post-disaster credit to a disaster region, relative to larger diversified banks.

This paper is most closely related to Gallagher and Hartley [2017] and Cortes and Strahan [2017], two highly cited studies that reach contrasting conclusions. 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.

This study differs from the existing literature in four main respects. First, we build a new database that allows us to link how a natural disaster affects the provision of new credit to a disaster region, how the provision of credit differs by the type of local banking institutions, and whether the type of banking institutions causally impact regional economic recovery. That is, we examine how bank type affects both credit and economic recovery in a single causal framework.

Second, we highlight and confront the serious identification issue in the literature, that the exogeneity of natural disasters alone does not solve endogeneity concerns surrounding the development of local banking institutions and post-disaster credit. The only other study in this literature that we are aware of that has addressed this concern is Morse [2011].

Third, we use FEMA administrative disaster cost data as a consistent measure for the severity, timing, and location of natural disasters. Our approach is in contrast to most of the literature that relies on disaster damage information from SHELDUS (SHELDUS [2025]).⁶ SHELDUS suffers from a severe, non-random missing data problem, even for very large events such as Presidential Disaster Declarations (Gallagher [2014]; Gallagher [2023]). The misidentification of large disasters is especially problematic in a setting characterized by repeat treatment (e.g. Dube et al. [2023]).

Fourth, we use LPDiD methods to estimate the impact of a natural disaster (Dube et al. [2023]; Roth Tran and Wilson [2024]). The model is robust to many of the critiques of the recent difference-in-differences literature (Abraham and Sun [2021]; Borusyak et al. [2021]). LPDiD is particularly well-suited to study the effects of natural disasters, as it provides a straightforward way to handle repeat treatment.

The rest of the paper proceeds as following. Section 2 outlines a theoretical framework to motivate our empirical model, briefly summarizes US bank deregulation, and describes our data. Section 3 discusses our statistical models and sample construction. Section 4 presents our results for how a natural disaster affects post-disaster bank credit. Section 5 documents our findings on post-disaster regional economic recovery. Section 6 concludes.

⁶Kim-Sherman and Seltzer [2025] provides a recent review of prominent finance papers that use SHELDUS data.

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, borrowers are modeled as entrepreneurs. Asymmetric information leads to a situation where lenders must spend capital in order to monitor borrowers and to determine if realized loan returns are due to the state of nature or borrower behavior. 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. In our setting, the risk that a homeowner will not repay is higher post-disaster. This is true because of the financial shock to the potential borrowers, and because there is less (or no) bank collateral due to damaged and destroyed homes (increasing moral hazard). The costly state verification model predicts that there would be a lower overall amount of credit to homeowners in a disaster region, and that some homeowners who would be expected to fully repay (e.g. proxied by credit score) will not receive credit.

The Townsend [1979] costly state verification 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.⁷ 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. In contrast, 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.

⁷We show that there is a high correlation between these types of lending activity during the time period when we have data on both home and business loans.

2.2 Bank Deregulation as a Source of Exogenous Local Banking

Local banking institutions are not randomly assigned geographically. Local bank development or persistence 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 negative economic shock of a natural disaster (e.g. Lackner [2019]; Roth Tran and Wilson [2024]). Econometric models that seek to estimate the causal effect of stronger local banking institutions, 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

Table 1: **Banking Deregulation by Year**

Deregulation Year	<u>States Enacting Deregulation</u>	
	Interstate Entry	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).

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).

The Riegle-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.⁸ 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.

An existing finance literature uses state-level banking deregulation as exogenous variation to examine various economic outcomes. These economic outcomes include per capita income (e.g. Berger et al. [2021]; Jayaratne and Strahan [1996]), income distribution (e.g. Beck et al. [2010]), firm innovation (e.g. Chava et al. [2013]), and educational attainment (e.g. Sun and Yannelis [2016]). A change in the amount or distribution of credit is the hypothesized mechanism (first stage) that affects the economic outcome in each paper. Appendix Table 5 lists highly cited papers that use state-level banking deregulation as exogenous variation to examine these outcomes.

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

⁸States 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]).

deposits for every bank and holding company operating in each county every year beginning in 1981. Unique FDIC identifiers track lenders across counties and years. We define a lender as each unique holding company, or as the company itself if it is not part of a holding company.

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

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

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

2.2.3 Deregulation and Local Banking

Figure 1 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.

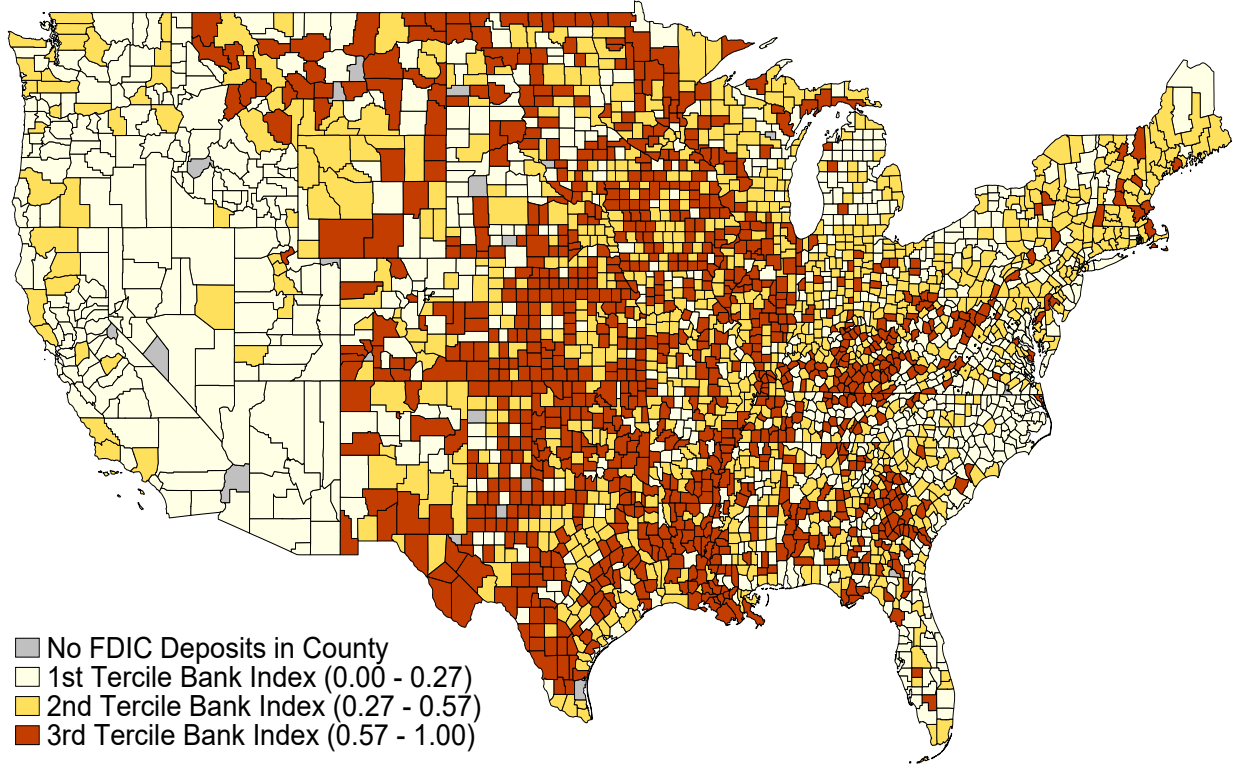
2.3.1 Natural Disaster Incidence and Cost

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 [2025]). Missing data in SHELDUS are pervasive and nonrandom (Gallagher [2023]).

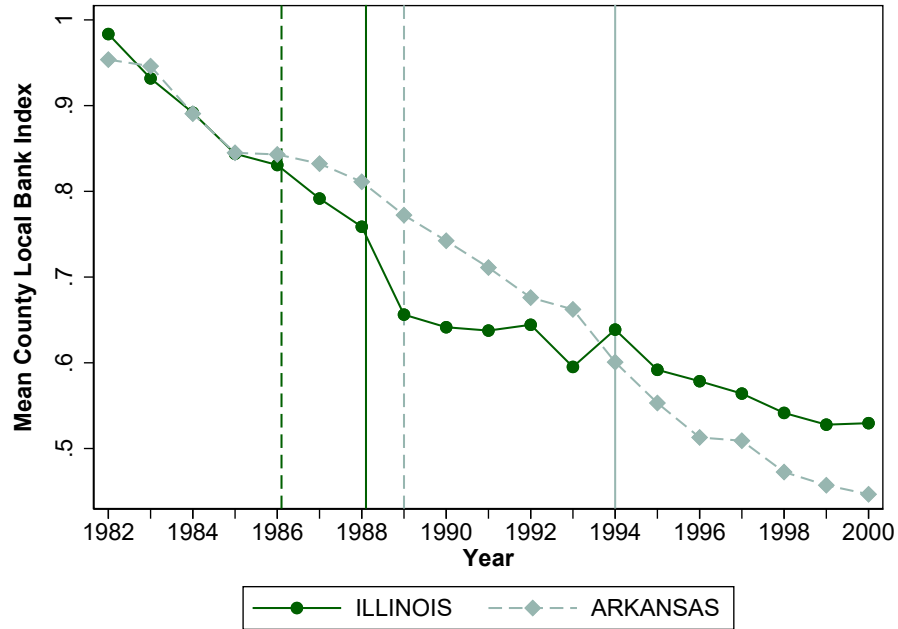
We use county-level Public Assistance data from 1990-2006 obtained through a Freedom of Information Act Request (FOIA). These data are geographically more precise than the publicly available information accessible through the databases linked to FEMA’s website. Only disaster-level (aggregated across 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

Figure 1: The Local Bank Index and State Banking Deregulation

Panel A. Local Banking Index, 1995



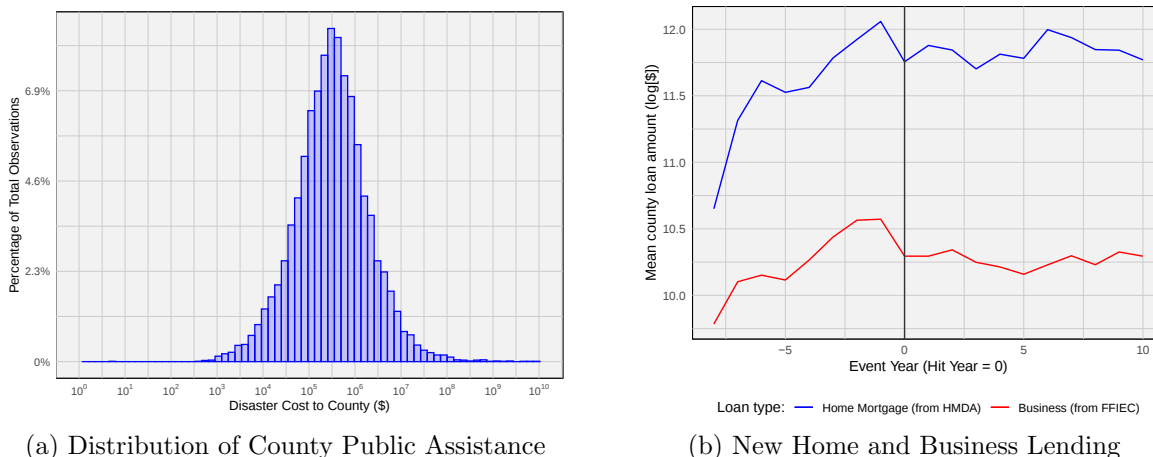
Panel B. Illinois and Arkansas 1982-2000



Notes: The county local bank indices in Panel A are for 1995, roughly the midpoint of our sample and the end of state-level deregulation. The indices are calculated following Equation 1 and then separated into three terciles. The points in Panel B are the mean county index for each state. The dashed (solid) vertical lines indicate passage of interstate (intrastate) deregulation. Data sources: FDIC; Morgan et al. (2004); Bisetti et al. (2020).

all PDDs during this time period).⁹

Figure 2: **Disaster Cost and Bank Lending Data**



Data sources: FEMA, FFIEC, HMDA.

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 HMDA data are available beginning in 1990. Business loan information is from the 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

⁹These 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.

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 [2024]). 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.¹⁰ 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 6 lists all of the data sources. Appendix Table 7 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-

¹⁰We thank the authors for sharing the SBA data for our use in this paper.

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. Estimating the impact of natural disasters in the US can be particularly challenging because it is a context characterized by repeat treatment. The median US county has three flood-related Presidential Disaster Declarations from 1990-2007 (Gallagher [2014]).

To address these limitations, we estimate a linear projections difference-in-differences model (Jorda [2005]; Dube et al. [2023]; Roth Tran and Wilson [2024]). 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 $h = 8$ years, as well as, two pre-disaster horizons $h = -2$ and $h = -3$ years. We estimate the equation separately for each horizon.

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

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.¹¹

¹¹The *OtherDisaster* variable also includes non-flooding PDDs for which we do not have county-specific cost. We consider two other definitions of a large disaster: above 50th percentile cost and 90th percentile cost (see Appendix

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 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

Figure 9). The impact on bank credit is somewhat smaller (relative to our 75th percentile baseline) when using the 50th percentile definition and approximately the same under the 90th percentile definition. 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 [2024]. Estimates for our coefficient of interest are largely insensitive to the choice of p (see Appendix Figure 10).

$LocalBanking_{c,\tau-1}$ 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.

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

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. It is well-recognized in the literature that there is a significant, lagged impact on the composition of regional banking institutions following interstate bank deregulation (e.g. Morgan et al. [2004]; Oberfield et al. [2024]. 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. All other variables in Equation 4 match those in Equation 3. Specifically, Equation 4 includes 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, $\widehat{LocalBanking}_{ct}$. A potential estimation concern is that $\widehat{LocalBanking}_{ct}$ 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 $\widehat{LocalBanking}_{ct}$ 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 LPDiD model. Leblebicioglu and Weinberger [2020] estimate a two-way fixed effects model that exploits the timing of interstate bank 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).¹²

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

¹²We estimate the model in Stata using the *csdid* package. We calculate the “simple” ATT across treatment groups and calendar time periods.

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 a 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.¹³ 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.

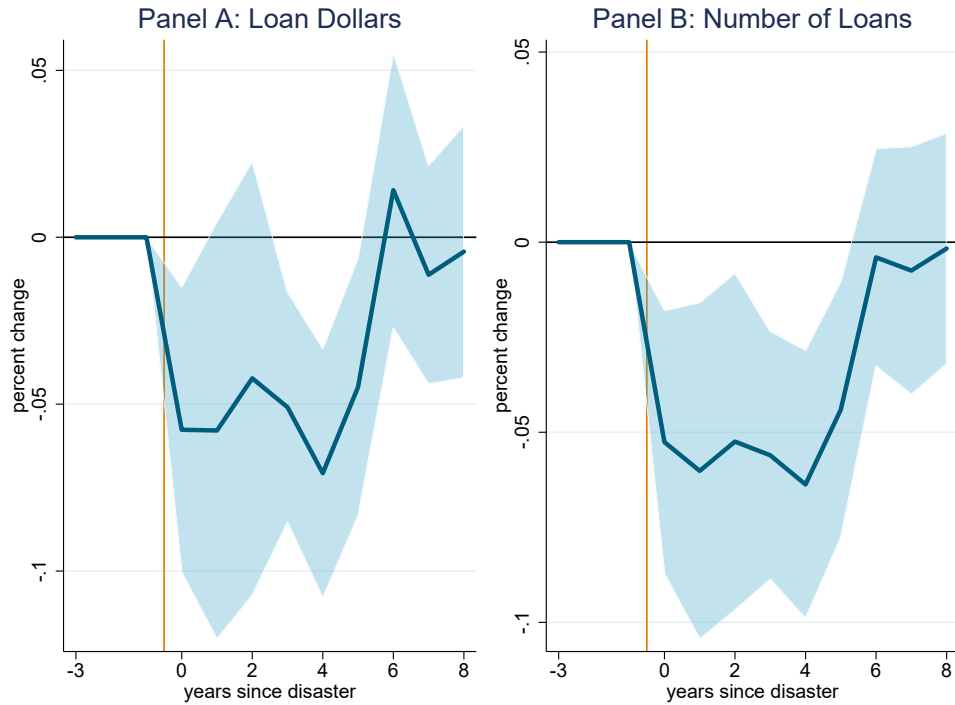
¹³There are 848 county-year observations in our sample in which the large disaster occurred eight years prior (and the calendar year is earlier than 2007).

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.

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



Notes: The figure plots two IRFs from estimating Equation 2. The figure shows the point estimates and 95% confidence intervals for the Large Disaster coefficient, β_0^h . The dependent variables are $\ln$ total loan amount (panel A) and $\ln$ total number of loans (panel B). Data sources: FEMA, HMDA.

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 Roth Tran and Wilson [2024] and Dube et al. [2023] and control for the lagged dependent variable in our specifications. For this

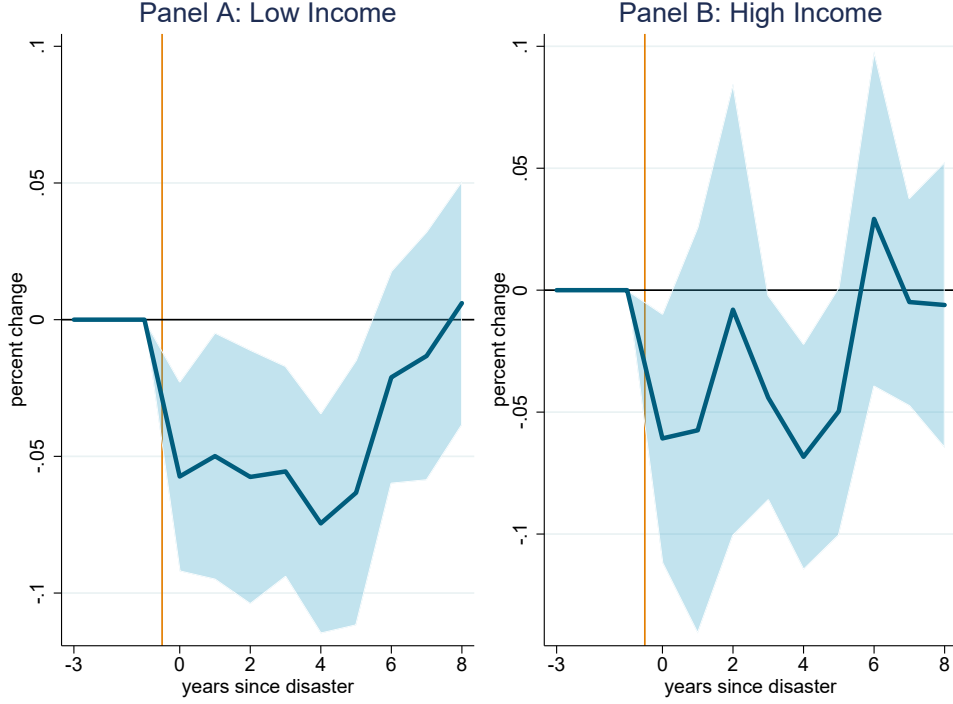
reason, the plotted coefficients in the figure are normalized to zero in the years before the large disaster.

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 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.¹⁴ 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.

¹⁴U.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>.

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



Notes: The figure plots two IRFs from estimating Equation 2. The dependent variable, $\ln$ total loan amount, is estimated separately for low- (panel A) and high- (panel B) income individuals. We define low- (high-) income individuals as those in the bottom (top) tercile among loan applicants. The figure shows the point estimates and 95% confidence intervals for the Large Disaster coefficient, β_0^h . 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, socioeconomic, and demographic conditions that influence the development of the banking institutions in a particular county.

Table 2 shows the results from estimating the first stage of 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 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.

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

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

Dependent Variable: County Local Banking Index			
Panel length:	<u>1981-2006</u>	<u>1990-2006</u>	<u>1990-2006</u>
	(1)	(2)	(3)
Interstate Indicator	-0.043*** (0.014)	-0.100** (0.048)	-0.099** (0.048)
Interstate Lag	0.005 (0.003)	-0.062* (0.039)	-0.061 (0.039)
Intrastate Indicator	-0.156*** (0.011)	-0.098*** (0.032)	-0.099*** (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

Notes: This table shows model estimates for the three deregulation variables from Equation 4. The dependent variable is the county-level local bank index (see Equation 1). Standard errors are clustered at the state-by-year level to match the level of the exogenous bank deregulation. Data Sources: FDIC, FEMA, Morgan et al. [2004], Bisetti et al. [2020]. Significance level: *** 1%, ** 5%, * 10%.

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 (%)
<u>A. Banking Index</u>						
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
<u>B. Instrumented Banking Index</u>						
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 (see Equation 1). 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.

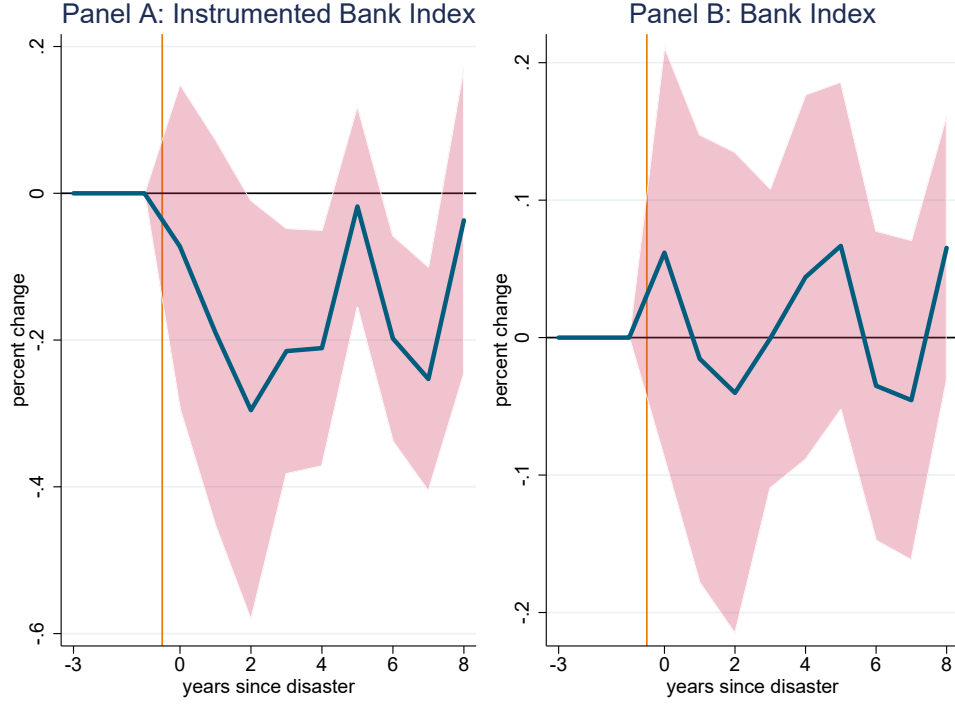
the instrumented banking index to isolate the role of local banks from the endogenous economic conditions that influence the composition of banking in a region.

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 average estimated coefficient ($\hat{\delta}^h$) over the first four years following the disaster is roughly -0.25. The 25th and 75th percentiles 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 25th and 75th percentiles of the instrumented banking index in the four years post-disaster is calculated by taking the difference in the interaction variable from the model, 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.¹⁵

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 for δ^h 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 using Equation 4 (panel A), or uses the raw index calculated from Equation 1 (panel B). 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.

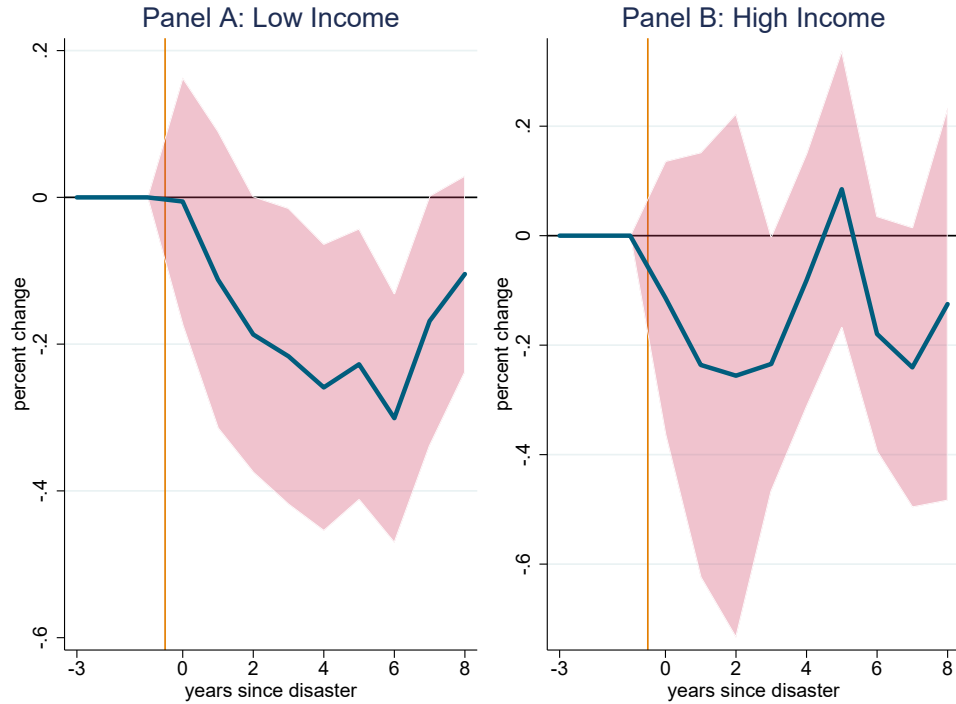
Appendix Figure 11 shows estimates from a robustness exercise examining how new credit varies when we estimate Equations 3 using a bank-level panel. Recall, our preferred model estimates a county-level panel. Our research questions are how new credit to a *region* following a natural disaster varies by the banking institutions, and how *regional* differences in new credit, attributable to the banking institutions, impact local economic recovery. A bank-level panel is not well-suited to

¹⁵The estimated *overall* lending effect from this model is calculated as: $\hat{\beta}_\tau^h + \delta^h * \widehat{LocalBanking}_{c,\tau-1}$. The estimated coefficients for a (non-interacted) large disaster, $\hat{\beta}_\tau^h$, are positive, but not statistically different from zero for the first five post-disaster years.

answer these questions. Still, Appendix Figure 11 shows that our baseline credit finding is similar when we estimate a bank-level panel.

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 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: 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 for δ^h from estimating Equation 3. The dependent variable, $\ln$ total loan amount, is estimated separately for low- (panel A) and high- (panel B) income individuals. We define low- (high-) income individuals as those in the bottom (top) tercile among loan applicants. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 6 shows the interaction coefficient of interest from estimating the change in loan dollars using Equation 3 when we instrument for local banking for the low- and high-income groups. 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.

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 interpret these findings as evidence of 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.¹⁶

Appendix Table 7 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.¹⁷ The relative size difference suggests that, at most, only a small fraction of private lending could be crowded out

¹⁶See 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.

¹⁷Hong et al. [2020] and Ouazad and Kahn [2022] also highlight the size and importance of private sector lending following a natural disaster.

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 private 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 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

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

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 12 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 12 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.¹⁸ 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.

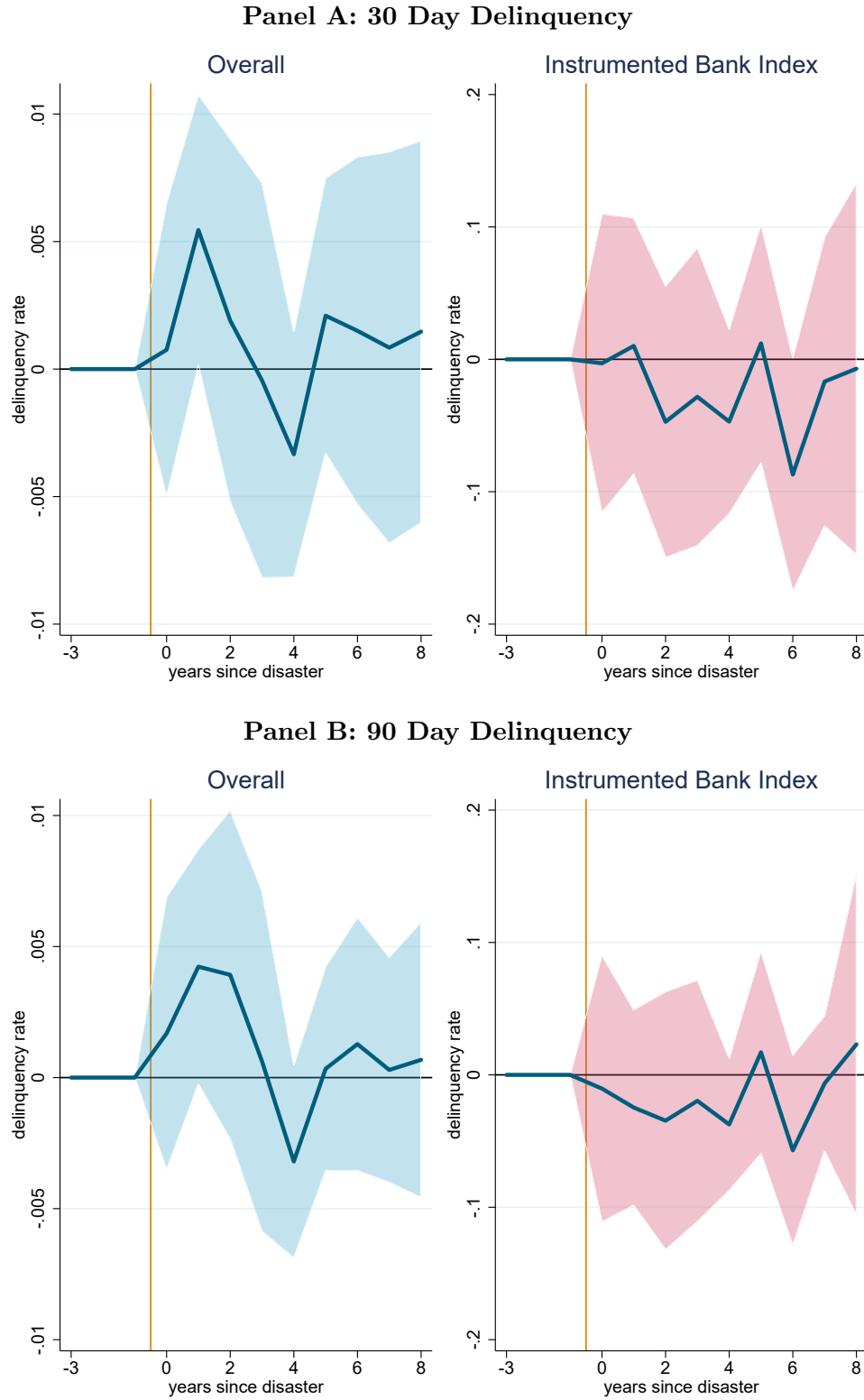
5 The Impact of Large Disasters on Local Economic Outcomes

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 [2024], 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 [2024] 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

¹⁸The percent increase is calculated relative to the mean in Appendix Table 7.

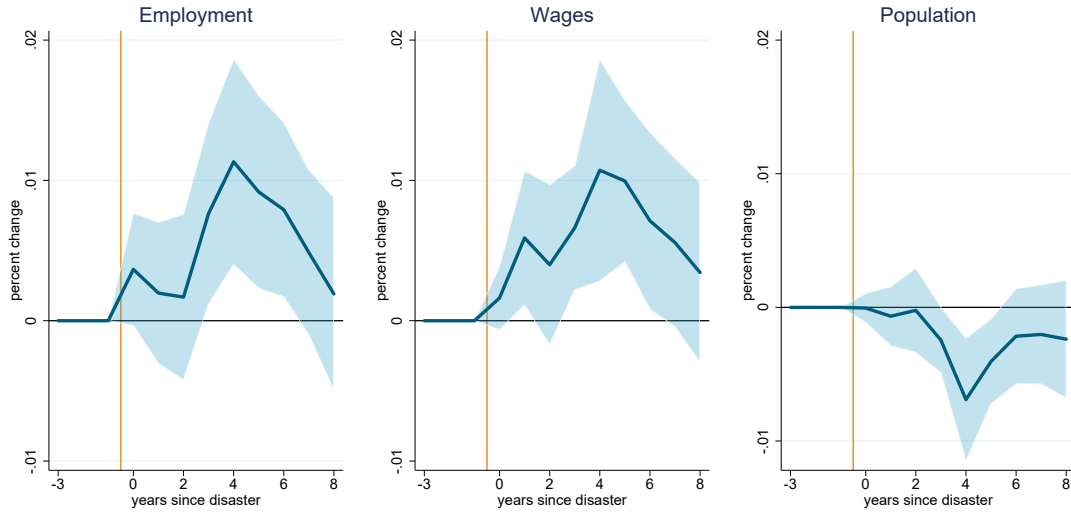
Figure 7: New Loan Delinquency for Home Loans Issued after a Large Disaster



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



Notes: 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.

affect post-disaster economic recovery. Wage and population growth appear to be lower in counties with greater local banking, but the confidence intervals generally contain zero. At the same time, there is some evidence for a temporary spike in employment immediately following a disaster in counties with greater local banking.

6 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 percentile cost threshold using verified damage to public infrastructure. Defining a large natural disaster in this way screens out counties with little damage that were included in a Presidential Disaster Declaration due to their proximity to more damaged counties 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.

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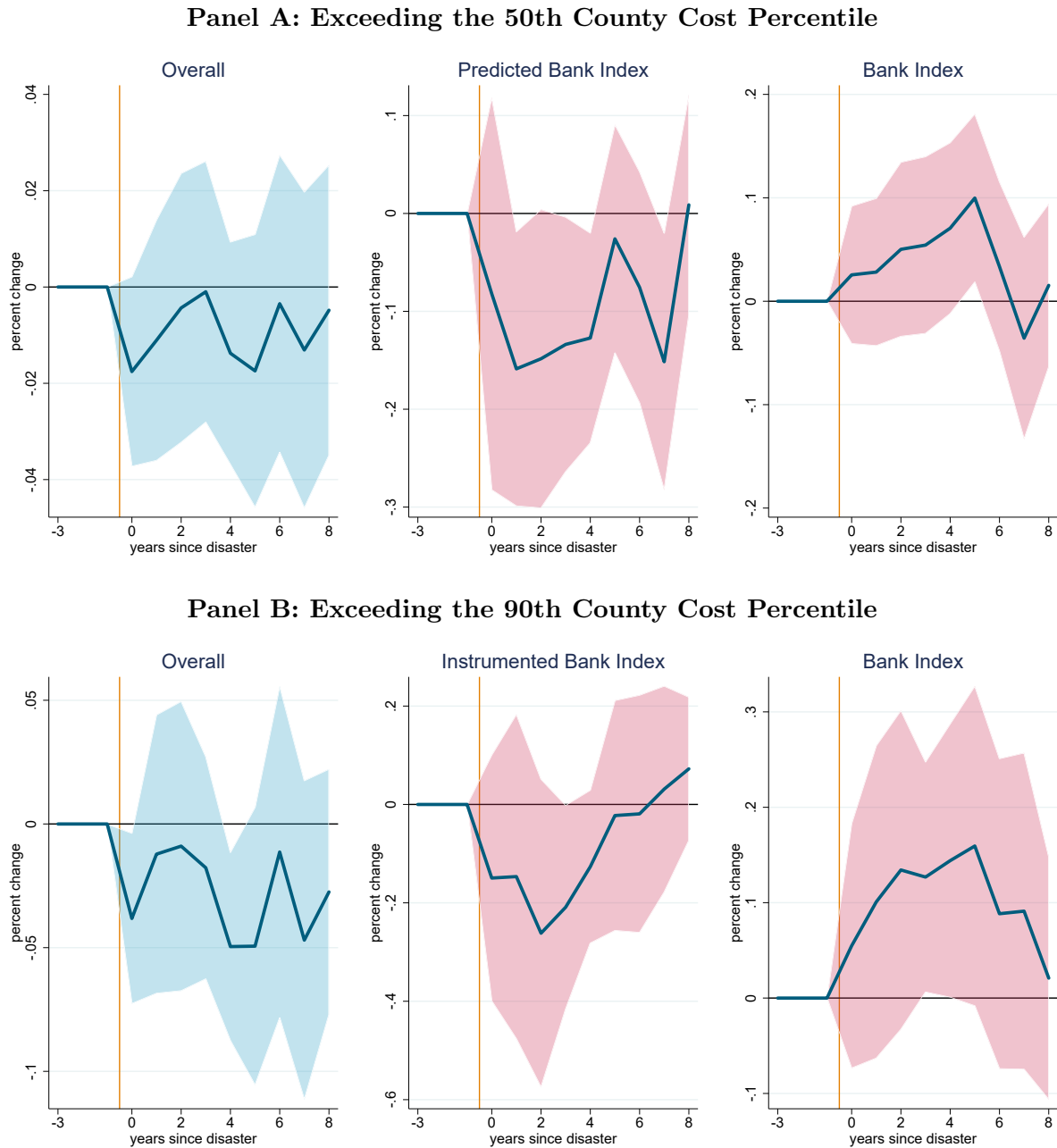
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8 Appendix

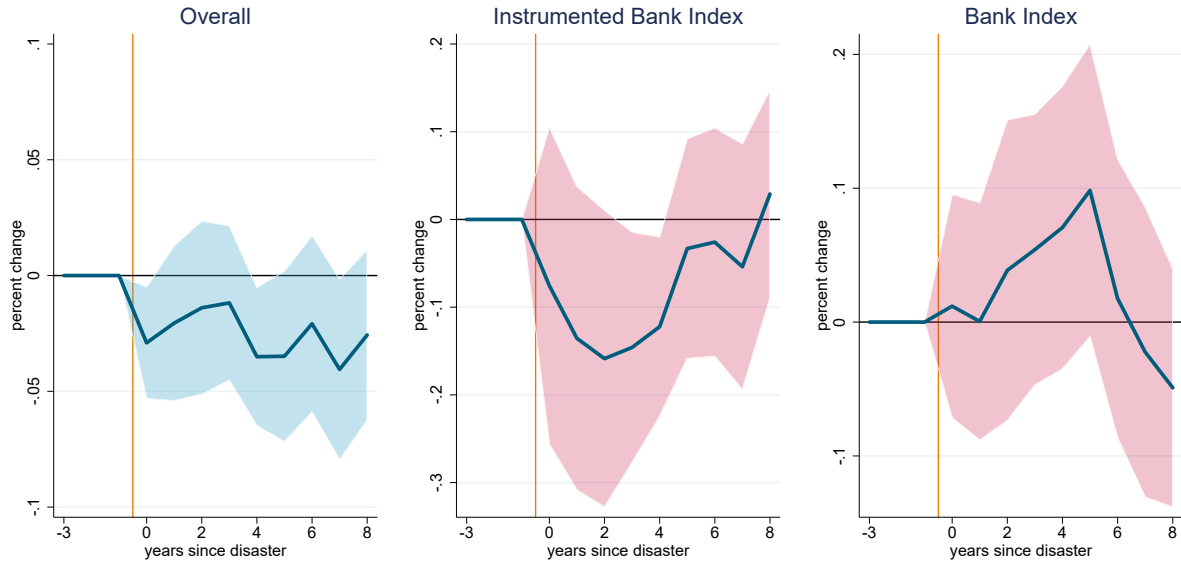
Figure 9: **New Lending following a Large Disaster: Robustness to the Definition of a Large Disaster**



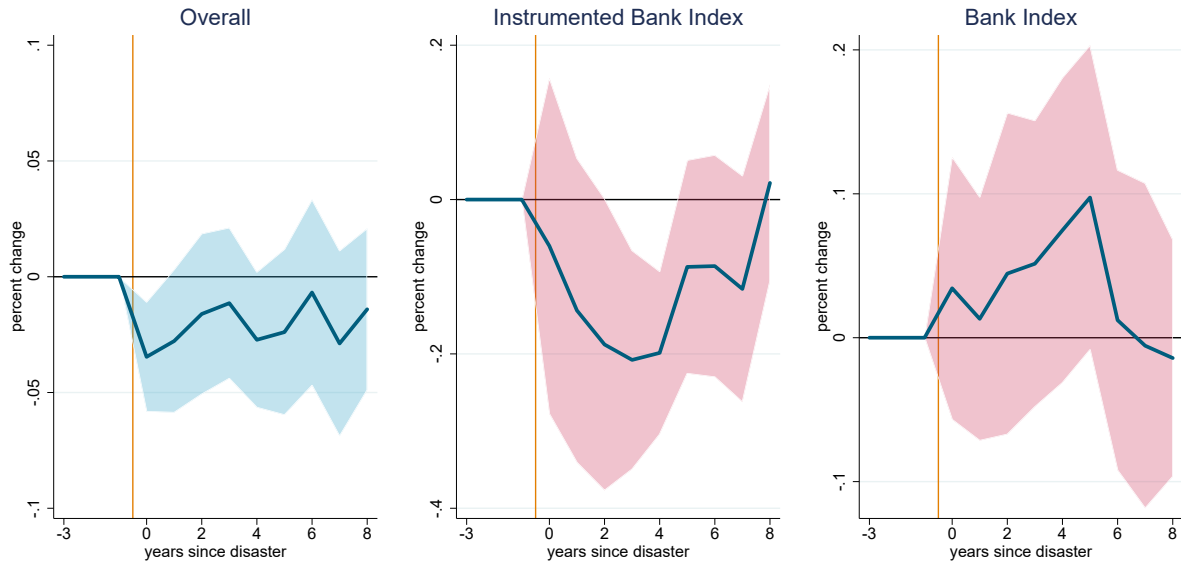
Notes: The figure plots IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable is $\ln$ total loan amount. Our baseline definition of a large disaster in the paper is one that exceeds the 75th percentile in county-level cost. By contrast, Panel A of this figure defines a large disaster as exceeding the 50th percentile, while Panel B defines a large disaster as exceeding the 90th percentile. The panels titled *Overall* in this figure are comparable to Figure 3 panel A. The *Instrumented Bank Index* and *Bank Index* panels are comparable to those in Figure 5. 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

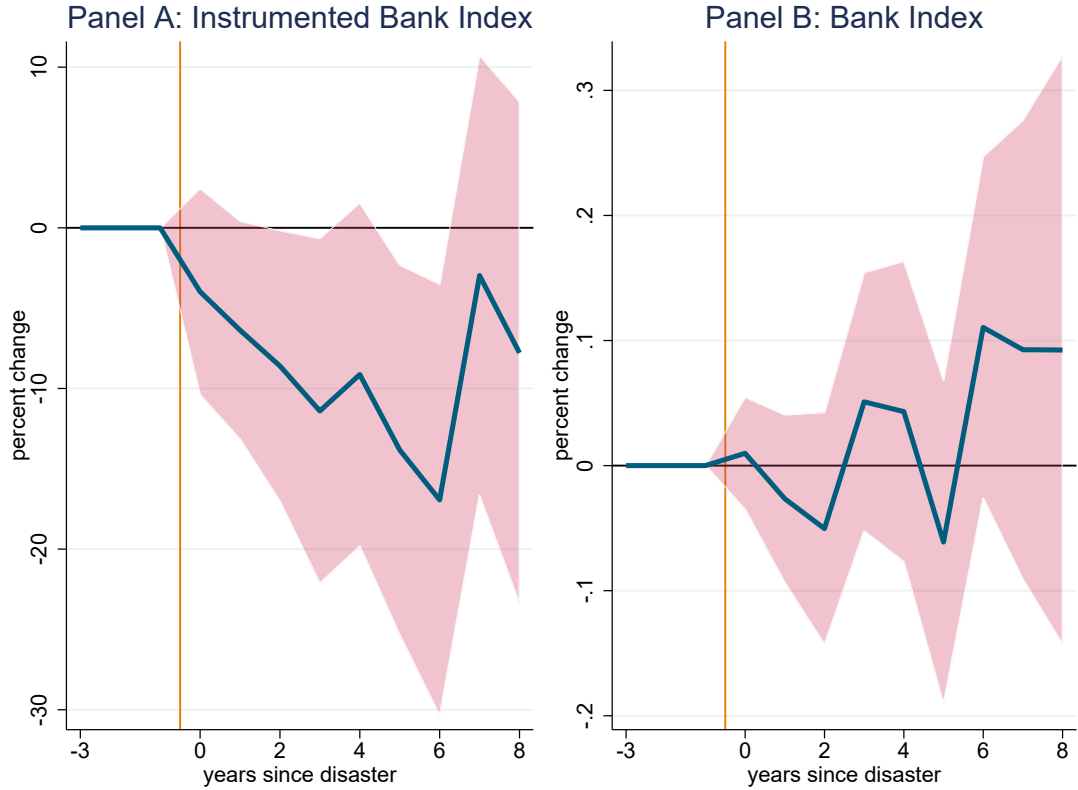


Panel B: Assume Disaster Impact Stabilizes after 10 Years



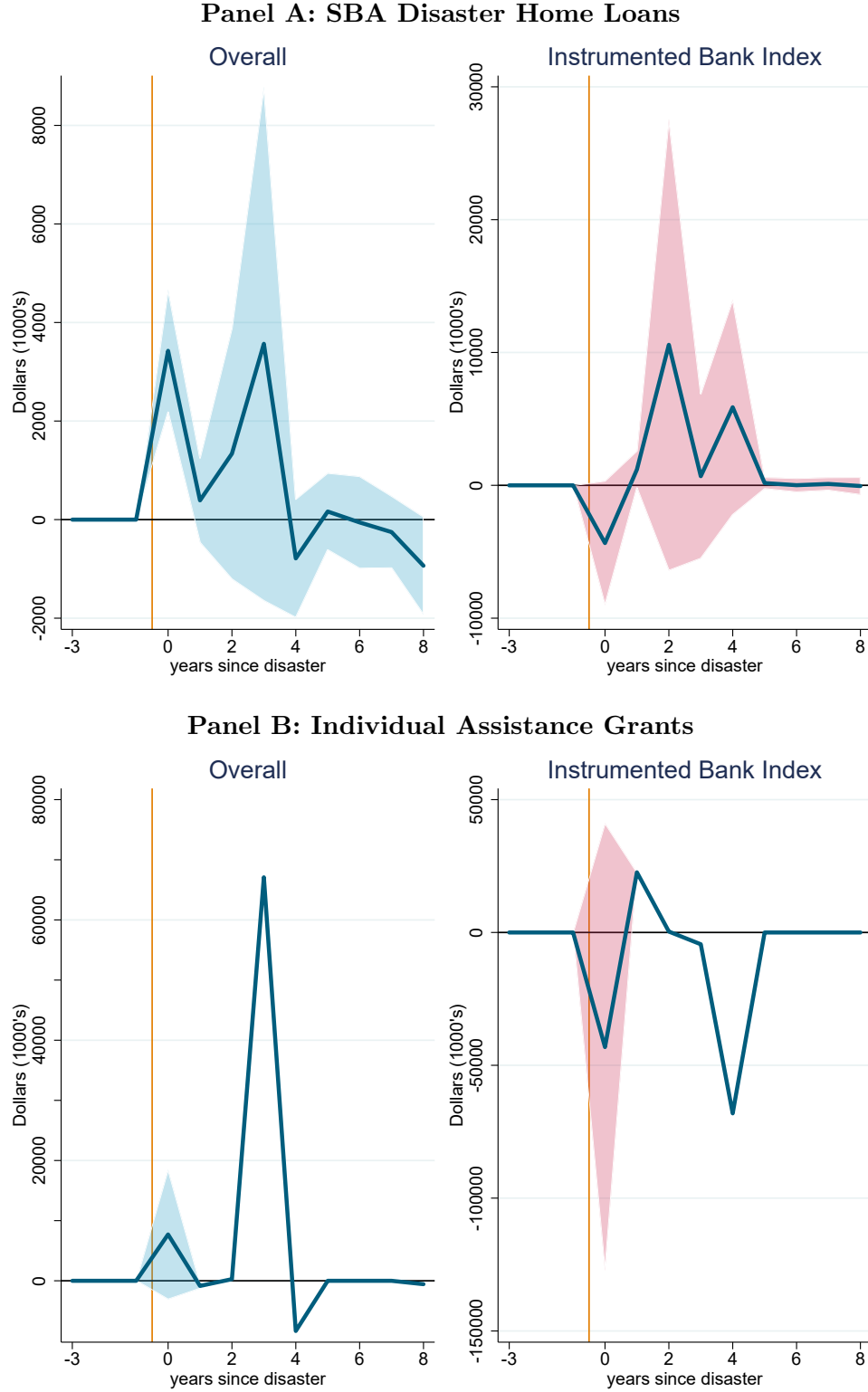
Notes: The figure plots IRFs (point estimates and 95% confidence intervals) from estimating Equation 2. The dependent variable is $\ln$ total loan amount. Our baseline model assumes that the impact of a large natural disaster stabilizes after five years. By contrast, Panel A in this figure assumes that the impact stabilizes immediately (zero years), while Panel B assumes that the impact stabilizes after ten years. The panels titled *Overall* are comparable to Figure 3 panel A. The *Instrumented Bank Index* and *Bank Index* panels are comparable to those in Figure 5. Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 11: New Home Loans after a Large Disaster by Level of Local Banking Index
Bank-level Model



Notes: The figure plots the Lender Localness by large disaster (interaction variable) point estimates and 95% confidence intervals from estimating Equation 3 using a bank-level panel. The dependent variable is $\ln$ total loan amount. The two panels differ by whether the model instruments for lender localness. Appendix Table 8 shows estimation results from estimating Equation 4 to predict bank-level Lender Localness (see Equation 1) using the bank-level panel. The results in this figure are similar to those in manuscript Figure 5 which estimates our preferred county-level model. We use the point estimates in Panel A to interpret how new lending differs by whether the bank is at the 25th and 75th quartiles of the estimated index. A move from the 25th to the 75th percentile implies an increase of 17 percentage points in new lending in the 3rd post-disaster year (calculated as $(-11.4 \times 0.336) - (-11.4 \times 0.351) = 0.17$). Data sources: FDIC, FEMA, HMDA, Morgan et al. [2004], Bisetti et al. [2020].

Figure 12: Direct Federal Disaster Assistance following a Large Disaster



Notes: 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: Literature that Estimates Economic Outcomes using State-Level Banking Deregulation

Paper	Journal	Dependent Variable	Independent Variable	1st Stage Model or Mechanism	Main Finding
Beck, Levine, Levkov (2010)	Journal of Finance	Income Distribution	State-level banking deregulation indicators	Reduced form models. Hypothesized mechanisms: Increased credit to individuals and entrepreneurs, lower credit cost for businesses	Reduction in income distribution
Berger et al. (2021)	Journal of Financial Intermediation	Per capita income	State-level banking deregulation indicators	Reduced form models. Hypothesized mechanism is via bank branching and improved access to credit	Increase in Economic Growth
Bisetti, Karolyi, Lewellen (2020)	Working Paper	Bank funding costs, net interest margins, profit	State-level banking deregulation (in- and out-state access)	Reduced form models. Hypothesized mechanism is bank market concentration	Higher funding costs, lower net interest margins and profitability
Chava, et al. (2013)	Journal of Financial Economics	Patents for young firms, Economic growth	State-level banking deregulation indicators	Reduced form models. Increase in access to credit for young, private firms most-likely to be engaged in exploratory (riskier) innovation	Increase (decrease) in innovation by firms when deregulation leads to less (more) local bank market power
Cornaggia, et al. (2014)	Journal of Financial Economics	State-level patents	State-level banking deregulation variable	Reduced form models. Hypothesized mechanism is an increase in bank credit to smaller, innovative firms	Increase (decrease) in private (public) firm innovation
Dick and Lehnert (2010)	Journal of Finance	Personal Bankruptcy	State-level banking deregulation indicators	Reduced form models. Mechanism: deregulation led to an increase in credit	Increase in personal bankruptcy
Jayarathne and Strahan (1996)	Quarterly Journal of Economics	State-level real per capita income	State-level banking deregulation indicators	Reduced form models. Hypothesized mechanisms are improved quality of bank lending (new credit) and increased quantity of credit	Increase in real per capita growth in income
Kerr and Nanda (2009)	Journal of Financial Economics	State-level number (new) establishments	State-level banking deregulation variables	Reduced form models. Hypothesized mechanism is improved credit markets	Increase in entrepreneurship rates and business closures
Levine, Lin, Xie (2020)	Management Science	Bank (liability) funding costs	Bank geographic expansion	Regress a Herfindahl Index of bank assets across states on a variable constructed using state deregulation and a geographic distance gravity model	Reduction in bank funding costs
Mayer (2024)	J. Financial and Quantitative Analysis	Credit (by high and low income)	Census Tract market share for larger banks	Regress large bank market share on distance to boarder for a sample of Census Tracts near state boarders that differ on bank regulatory restrictions	Decrease in credit for low-income households
Morgan, Rime, Strahan (2004)	Quarterly Journal of Economics	State-level economic volatility	Measures of interstate bank integration	Regress measures of bank interstate integration on state deregulation indicators	Reduction in state-level economic growth volatility
Sun and Yannelis (2016)	Review of Economics and Statistics	Educational loans and attainment	State-level banking deregulation indicators	Reduced from models. Show evidence for an increase in credit (loans to students)	Increase in college enrollment

Notes: The table includes highly cited studies (excluding review-style articles) from a Google Scholar search on December 12, 2024 for “the effect of state banking deregulation”. Additionally, the table includes two studies, Morgan et al. [2004] and Bisetti et al. [2020], which are the basis of our instrument, and one study, Mayer [2024], which is closely related to our (robustness) bank-level regressions.

Table 6: 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).

Notes: Section 2 provides details on our data sources.

Table 7: Summary Statistics

	<u>1990</u>		<u>2007</u>		<u>1990-2007</u>	
	Mean	Median	Mean	Median	Mean	Median
<u>I. Loan Information</u>						
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
<u>II. Economic Information</u>						
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
<u>III. Disaster Information⁴</u>						
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

Notes: 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 6): ¹business loan data (1997), ²SBA disaster home loans (1991), ³delinquency rate (1999). ⁴The 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.

Table 8: Predicting the Lender Localness Ratio

Dependent Variable: Lender Localness Ratio			
Panel length:	<u>1981-2006</u>	<u>1990-2006</u>	<u>1990-2006</u>
	(1)	(2)	(3)
Interstate Indicator	-0.044*** (0.014)	-0.085 (0.060)	-0.081 (0.061)
Interstate Lag	0.018*** (0.003)	-0.004 (0.058)	-0.002 (0.058)
Intrastate Indicator	-0.174*** (0.012)	-0.102*** (0.036)	-0.101*** (0.035)
Disaster Indicators	X	X	X
County FE	X	X	X
Year FE	X	X	X
Drop Repeat Disaster Obs			X
R ²	0.248	0.215	0.212
Observations	481,639	375,819	347,423

Notes: This table shows model estimates for the three deregulation variables from Equation 4. The dependent variable is the lender local bank index (see Equation 1). The key difference between this table and Table 2 is the structure of the panel data used to estimate the model. Table 2 displays estimates from our preferred county-by-year panel, whereas the results in this table are from estimating a bank-by-year panel. The dependent variable in Table 2 is the county-level local bank index that aggregates the lender local bank indices to the county-level. Sources: Bisetti et al. [2020], FDIC, FEMA, Morgan et al. [2004]. Standard errors are clustered at the state-by-year level to match the level of the exogenous bank deregulation. Significance level: *** 1%, ** 5%, * 10%.