The Economic Impact of Natural Hazards in the US: Does Local Finance Matter?

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Abstract

I study the employment impact of natural hazards and the role of the banking industry in improving resilience. I assemble a novel dataset of losses in US coastal state counties during 1998-2019. My analysis incorporates weather risk and addresses concerns that the local banking structure is endogenous with respect to the likelihood of disasters. Local finance exacerbates the disaster-driven job contractions and limits resilience in counties with: i) higher risk – where overall damage is higher; ii) higher income – where the local population may rely more on private credit; ii) more risky industry sectors – where local lenders can suffer higher loan losses. Diversified, non-local banks are not subject to significant losses and increase lending post disaster, which can explain why counties with more non-local lenders have faster growth and improved resilience.

JEL Classification: R11, R12, G21

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1 Introduction

Natural hazards reduce economic activity because businesses are vulnerable to severe weather.[1] While access to credit has been shown to improve resilience, it is not clear which lenders are in a better position to provide credit.[2] Geographically diversified lenders can be critical for economic resilience because they can avoid systemic portfolio losses, but they can also limit originations if collateral damage reduces the profitability of new loans.[3] Local lenders may be less sensitive to collateral values due to their specialization and proximity to businesses but their geographical concentration can expose them to significant losses after landfall.[4]

Can non-diversified lenders improve local economic resilience or do they amplify the negative shock? How important are portfolio losses and borrower risk after landfall? To answer these, I assemble a novel dataset of losses in US coastal state counties during 1998-2019. Unlike other studies, I account for the likelihood of weather-related damages (weather risk) using learning algorithm predictions, based on 70 variables reflecting the vulnerability of residents to natural hazards and the frequency of severe weather. The sample stacks event studies that include three-month employment growth at the two-digit industry for the quarter before and two quarters after each disaster. To distinguish which counties have access to local finance, I measure the proportion of deposits in highly concentrated banks.

Using a dynamic difference-in-means specification, I first evaluate the employment effect of above-median losses (treatment) for the average industry, for counties of different risk, different economic development, and for individual industries. After that, I use a difference-in-difference specification to examine whether the employment growth differs between treated and non-treated counties and between those with and without high local finance, after controlling for county-industry-event and industry-state-time-event fixed effects. Finally, I turn to a bank sample of lending and performance observations and identify how increasing ex-

[1]See Strobl (2011); Kroll et al. (1991); Dahlhamer and Tierney (1998); Webb et al. (2000)
[2]Noy (2009) discusses the benefit of access to finance.
[3]See, for example, Emmons et al. (2004); Aubuchon et al. (2010) and Berrospide et al. (2016).
[4]See Berg and Schrader (2012) and Bolton et al. (2016).

posure to disasters affects local and non-local lenders in the short period after the landfall.

The explicit measure of risk helps me limit the concern that treated counties have different industries, expectations, disaster preparedness, infrastructure, and different prevalence of local lenders. I do this by comparing employment and bank outcomes across counties with similar weather risk and economic development. Indeed, without such matching treated counties tend to have higher loss, lower income, and higher prevalence of local lenders. These differences disappear when counties are matched by risk and income, allowing me to identify the role of local finance across treated counties with similar characteristics.

My results suggest that mixing counties with different levels of risk and economic development in the comparison groups – as is common in the literature – will overestimate the employment impact of natural disasters by close to half. My preferred specification implies that the average industry job growth declines by 0.33% compared to 0.48% in the baseline. I find that job growth declines primarily in high-risk counties, with the majority of the impact concentrated in the higher-income bracket, across the Information, Leisure and Hospitality, Other Services, and Trade, Transportation and Utilities sectors.

Can a banking industry oriented towards the local economy mitigate this employment shock? The evidence consistently shows that local finance exacerbates rather than improves disaster-driven job contractions. In fact, once I account for the banking industry, the employment effect dissipates for low-local-finance counties, while for high-local-finance areas it remains between 0.5% and 0.62%. The difference in the way counties recover when local lenders dominate the financial intermediary sector is most evident with: i) higher risk – where overall damage is higher; ii) higher income – where residents rely more on private credit; ii) more risky industry sectors – where local lenders can suffer higher loan losses.

The interaction of disasters and the local banking industry has not been widely examined and we know little about the impact on credit market conditions. The limited existing evidence suggests that un-diversified lenders improve recoveries. Cortés (2014) finds that local finance improves new/small firms' job growth after natural hazards. Schüwer et al.

(2019) document that markets with more independent lenders have faster growth after hurricane Katrina. Cross-country studies show that the financial sector development improves recoveries but there is also evidence that disasters, themselves, can directly impact lenders.[5]

To understand the channel through which local and non-local lenders affect the recovery, I study how different levels of systemic exposure to disasters affects the performance and loan volumes of individual banks. The evidence from two different regression models suggests that non-diversified local lenders with exposure to high-impact disasters reduce lending. Importantly, this reduction is accompanied by higher losses in the loan portfolio, indicating that local lenders focus on rebuilding capital and managing risk rather than on expanding credit. In contrast, I find that diversified non-local banks which are not subject to significant losses or higher default risk increase lending post disaster, which can explain why counties with more non-local lenders have faster employment growth.

The debate about concentrated lenders is not new and has been covered in the bank diversification literature, which studies how the spread of lender's portfolio across several markets impacts economic volatility. Morgan et al. (2004) suggests that single-market lenders amplify economic shocks that limit bank's funding, e.g. due to portfolio losses. Alternatively, such lenders can limit the impact of economic shocks when they mostly reduce the creditworthiness of new borrowers, e.g due to destruction of collateral.[6] My analysis indicates the local banking structure does not matter in cases of mild losses, in low-risk counties, or in low-income counties. However, following severe losses, access to non-local lenders significantly improves the resilience of the local economy. This suggests that the increase of uncertainty about the creditworthiness of new borrowers is a relatively less important friction for the impacted counties compared to the capacity of the financial intermediaries to provide credit.

[5]For the financial sector role, see Noy (2009), McDermott et al. (2014), Felbermayr and Gröschl (2014),Keerthiratne and Tol (2017), Del Ninno et al. (2003). Duqi et al. (2021) finds that competition matters. For the effect of disasters on lenders, see Berg and Schrader (2012), Koetter et al. (2019), Cortés and Strahan (2017), Hosono et al. (2016), and Collier and Babich (2019).

[6]There is new evidence of a trade-off between the scale economies from a diversified portfolio and diseconomies due to the limited capacity to process soft information. Because this limits portfolio losses during a negative shock, the overall effect of local lenders is to improve economic volatility. This tradeoff is discussed by Acharya et al. (2006) and Tabak et al. (2011).

My key contributions are threefold. First, I explicitly incorporate the risk of severe weather in my analysis and address concerns that the local banking structure is affected by the likelihood of severe disasters.[7] Indeed, I show that risk and local finance are not independent and, by extension, the likelihood of treatment is related to the banking structure. Importantly, once counties are matched by risk this difference disappears. This adjustment has a non-trivial effect on the estimated impact of disasters and of local lenders. Second, I provide the first extensive study of the employment effect of natural hazards for an extended period and significant part of the US which distinguishes individual industries. The existing literature either focuses in detail on the sector-specific impact of one disaster (Meltzer et al., 2021) or examines the aggregate county impact over a long period (Strobl, 2011). My approach links the two literatures and suggests that the decline in the sectors identified in the first literature can explain the aggregate dynamic. Third, I provide both employment and bank evidence that local lenders can exacerbate the negative shock from severe disasters. I argue that local lenders experience more defaults due to their systemic exposure and limit loan originations. This result contrasts with the widely accepted findings in Cortés (2014) and Schüwer et al. (2019) that local, independent lenders promote economic resilience.

The rest of the paper proceeds as follows: section 2 discusses related literature, section 3 details the data, section 4 considers the employment impact of natural hazards, section 5 explores the role of local lenders, section 6 provides bank-level evidence. Section 7 includes robustness evidence and section 8 concludes.

2 Related Literature

My results are relevant for the literature on the local economic resilience to natural hazards. There is a consensus that firms are vulnerable to natural hazards but employment effects are transitory (Xiao and Nilawar, 2013) and sector-specific (Guimaraes et al., 1993). Local

[7]For example, if only national chains are able to survive substantial losses (Basker and Miranda, 2018), and they rely on non-local lenders, then the risk of losses can reshape both the local economy and the prevalence of local lenders.

economies, as a whole, are resilient to natural hazards (Xiao and Feser, 2014) but smaller firms, in industries requiring a store front take the brunt (Basker and Miranda, 2018; Meltzer et al., 2021).[8] I find evidence in support of this and also argue that the composition of financial intermediaries is a key reason for resilience.

My results are relevant for the distinct literatures that explore the nexus between natural hazards and financial intermediaries. Starting with Noy (2009), there is cross-county evidence that the development of the financial sector plays are role in recovery from disasters. Micro evidence explains this with the ability of multi-market banks to allocate funding to areas with high demand (Cortés and Strahan, 2017; Koetter et al., 2019), with single-market banks' information advantage (Cortés, 2014) or better capitalization (Schüwer et al., 2019). However, there is evidence that disasters can increases the probability of bank default (Klomp, 2014), due to reduction in capital (Collier and Babich, 2019) or in deposits (Brei et al., 2019), and that risk of new loans can increase (Berg and Schrader, 2012). My results add to this literature by showing that natural hazards can have heterogeneous effect on banks' credit supply depending on the systemic portfolio risk. I show that the lending capacity of concentrated lenders with high local market exposure can be compromised after landfall, which can explain why multi-market lenders have been shown to improve recovery.

I also relate to the literatures on bank diversification and relationship lending. There is limited consensus on the benefits to banks of geographic diversification, as it can reduce the cross-market correlation of returns (Goetz et al., 2016) or increase risk-taking (Demsetz and Strahan, 1997). Additionally, small local lenders are not sensitive to local economic conditions (Yeager, 2004), as a result of their more prudent lending practices (Stever, 2007). This may be due to relationship lending which shelters borrowers during economic turbulence (Bolton et al., 2016). My results support Berger et al. (2020), which finds that smaller lenders can exacerbate negative shocks by reducing lending to more risky businesses.

[8] There is contrasting evidence of a longer-lasting impact in Belasen and Polachek (2008) and Belasen and Dai (2014).

3 Data and Sample Selection

The sample focuses on 825 counties in 14 US eastern and southern coastal states during 1998 to 2019. Each county experiences a varying amount of damage from a combination of hurricanes, floods, or severe storms, with the majority being caused by hurricanes.[9]

Losses: I use a novel measure of county losses that combines damage information specific to each county and to each disaster declaration. It comes from data pertaining to four distinct programs, as follows. First, the Individuals and Households Program (IHP) lists damage assessed by property surveyors for uninsured residents in need of emergency repairs and relocation. Second, Small Business Administration's (SBA) Disaster Loans program details residential and commercial losses to property/contents for those who borrow to finance repairs. Third, FEMA's Public Assistance (PA) program estimates losses to public property, including roads, bridges, and hospitals.[10] Fourth, National Flood Insurance Program (NFIP) lists insured flood-related losses based on residential/commercial insurance claims.[11] I add up losses for each county from each source and scale the total by county income in the previous year. Summary statistics are listed in Table 1. The average loss in the sample is 0.5% of county income, with interquartile range between 0.01% and 0.3%. The top left map in Figure 1 highlights the spatial distribution of the events in the sample by measuring the total number of events for each county during the sample.

Risk of Severe Weather Losses: I use predictions of expected loss from natural hazards following the procedure outlined in Petkov (2022). The predictions are based on the Random Forest (RF) learning algorithm, which is executed separately for each state in the sample. The algorithm predicts five-year losses on the basis of 70 variables that capture the level of

[9] Table A1 in the Appendix lists the states included in the sample and outlines the proportion of events that are related to hurricanes.

[10] A big component of this is related to the cost of cleanup of debris, which represents a key loss from natural hazards. I use PA data which lists individual counties as recipients under a given disaster declaration.

[11] I match a flood loss to a disaster declaration if it occurred within 30 days of the initial declaration date. In the case when there are more than one declarations within the county, I use the first event. Finally, I drop flood claims of less than $100 and drop counties with less than $50K in total claims.

resident vulnerability to natural hazards and the frequency of severe weather in each area.[12] I use the median of the predicted loss for each county over the sample period and define risk categories relative to all counties in each state. The above-median (high-risk) and below-median (low-risk) categories reflect levels of expected loss given the resident vulnerability and frequency of severe weather. They capture weather risk, which can be defined as the potential for damage to the local housing, infrastructure, and businesses. The third map in Figure 1 plots the risk categories in the sample. There are clear clusters of high-risk coastal counties and clusters of low-risk counties which are far from water.

Employment: Monthly industry-specific employment data comes from the U.S. Bureau of Labor Statistics (BLS). Sectors are divided into two-digit NAICS groups. The monthly data allows me to flexibly define quarterly employment growth relative to the month of each specific natural hazard. The empirical analysis uses employment growth (by industry) based on 3-month growth rates right before/after the occurrence of each event. At this frequency, employment at the average industry grows by 0.4%, with a standard deviation of 13.7% (see Table 1). Table 2 reports the full list of all industry sectors. We can see that growth rates can vary substantially across sectors, reflecting differences in the relative size and local demand trends. To minimize the importance of such variation all employment regressions are weighted by the six-month lag of employment.

Measure of Local Finance: The proxy for the prevalence of local finance uses the definition of community banks from Meyer and Yeager (2001) and Cortés (2014). Banks are assumed to be local if more than 66% of their deposits are located in one county. Information about the geographic distribution of deposits comes from the Summary of Deposits. This definition focuses on lenders with particularly concentrated portfolios for which the landfall of natural disasters can represent a systemic event that can disrupt credit supply. The county where

[12]The variables include: 15 lags of disaster declarations for hurricanes, flooding, and severe storms; 11 variables for the fraction of housing in A, B, X flood-zones, fraction of insured in each zone, Community Rating System discount in each zone, and fraction of housing within 200 and 2000 yards of water; 44 demographic/housing variables from the 2000 US census. For more information about the procedure and about each of the variables please consult Petkov (2022).

the bank has the majority of deposits is the bank's home and its deposits in this county are defined as local. I measure the proportion of local deposits relative to the total for each county and designate the counties above the state median as having higher access to local finance. This produces a balanced split of Low-High Local Finance counties, as can be seen in Table 1.[13] The fourth map in Figure 1 plots the spatial distribution of local finance.

Bank Data: Quarterly balance sheet data for different lenders comes from Call Reports. Table 3 provides summary statistics for key variables in the bank-level analysis. Note that 43% of observations in the bank sample are of lenders which are defined as local.

Sample Description: The structure of the employment and bank sample differs from the standard panel datasets used in the literature. I do not rely on a balanced panel of county-industry-month observations but, instead, focus only on the short periods surrounding each disaster and compile a sample of stacked event studies. The included events are county-specific and comprise of the four months before a disaster as well as the seven months post disaster. In the cases when the following seven months feature a second disaster (or more), the event is expanded to the second post period.

In the case of employment data, I focus on the 3-month jobs growth in the third month after the disaster – i.e. first quarter, and the sixth month after – i.e. second quarter, and compare to the growth at month zero right before the landfall – i.e. pre-quarter. In the case of bank data, which is reported for each quarter, I match the closest pre and post quarters relative to the month of the landfall.

This definition of the sample has important implications. First, only counties that are subject to positive loss are used in the analysis. Therefore, the research design identifies the employment effect of higher loss compared to lower one, and not relative to unaffected counties. Second, I focus on relatively short-term dynamics of employment and lending. I exclude unaffected counties in order to limit the heterogeneity across the comparison groups in the empirical analysis. Disasters usually have a high impact on a cluster of counties and

[13]The average share of local deposits is 24%.

a lower impact on the surrounding areas. A comparison between high- and low-impacted counties from the same event, will, therefore, include a well-defined area within each state that is part of the same local economy, subject to similar economic, geographic, and demographic factors. I focus on the short period surrounding each disaster in order to keep the size of the sample tractable and following the existing literature, which suggests that most of the impact is contained within several months after landfall (Cortés and Strahan, 2017).

Finally, the sample excludes counties with population below 10,000 and county-industries which employ less than 200 in the year preceding a landfall. Also excluded from the sample are counties without a flood zone. House fractions in flood zones are a key driver in the prediction of losses from severe weather in the RF learning algorithm. The lack of flood zone data makes the risk designation highly speculative. Lastly, I excludes counties with total damage in the top 1% of the distribution across all counties with positive loss. These areas experience extreme loss and employment recovery is likely to follow a particularly distinct trajectory of long-term recovery.

Descriptive Statistics and Maps: Table 1 provides some basic statistics for the key variables in the analysis of employment. These are further divided by whether they come from treated counties, which are those with above median losses. Treated counties experience on average 0.6% more losses than the control counties (0.8% vs 0.2%), with the majority of the latter having less than 0.1% of losses according to the interquartile range. The majority of treated areas in Figure 1 are coastal counties, while the control areas are dispersed across the state.[14] The sample is closely split between high/low risk and treated areas are more likely to be of high-risk type (63% of these are high-risk vs 46% of the control). Treated counties are less likely to be high-income – 35% of them have high GDP level compared to 47% of the control. The local share of deposits – the measure of access to local finance – is slightly higher in treated counties leading to slightly higher proportion of counties designated as High Local Finance.

[14]Note that some counties are treated more than once during the sample period of 22 years.

Employment growth for the average industry declines by 0.5% during the two quarters following a natural hazard. The decrease is higher for treated counties: 0.7% compared to 0.3% for the control. Table 2 breaks down employment growth by industry. Growth declines in treated counties are observed for: financial activities, leisure and hospitality, manufacturing, and other services. Interestingly, growth improves for: education and health services, and trade, transportation, and utilities.

4 Employment Impact of Natural Hazards

Natural hazards can impact employment indirectly through their effect on fixed assets which are vulnerable to severe weather and can also disrupt labor supply directly – due to injuries or out-migration. Upstream disruptions or infrastructure damage limit lifelines and cause indirect losses. Prolonged closures reduce customers by redirecting demand elsewhere. All of these can reduce employment after a landfall.

To measure the average employment impact of disasters, I start by comparing industry-specific employment growth at counties with above-median loss relative to those with positive but below-median loss. This approach uses a simple difference-in-means empirical methodology to identify the impact of substantial disaster-generated loss on employment growth. I focus on 3-month differences in labor outcomes – during the two quarters following the landfall, and also highlight the month-by-month impact for up to seven months after.[15]

Table 1 reveals two dimensions of underlying heterogeneity that exists between treated and control counties: i) treated counties are more high risk; ii) control counties have higher income. Both can affect labor market outcomes by introducing differences between treated and untreated counties in terms of the distribution of industries, the preparedness of the local businesses and infrastructure, and local expectations. The empirical design discussed below attempts to address these concerns by relying on a quasi-experimental design setting

[15] The short-run focus is consistent with other studies of the impact of natural hazards, such as Strobl (2011) and Cortés and Strahan (2017).

which compares county-industries residing in areas with similar underlying risk and income.

Empirical Methodology

I estimate an event-study specification using a sample of stacked quarterly employment growth observations for the quarter before and two quarters after the landfall of the natural hazard. The regression model is as follows:

$$\Delta \ln \mathrm{Emp}_{cite} = \sum_{j=\{3,6\}} \beta_j \mathrm{I(t{=}j)} \times \mathrm{I(Loss{>}Med)}_{ce} + \alpha_{cie} + \gamma_{iste} + \epsilon_{cite} \tag{1}$$

where $\Delta \ln \mathrm{Emp}_{cite}$ is the three-month log employment difference in industry i in county c during month t of natural hazard event e. I(t=j) are indicators for time relative to the natural hazard and $j = 0$ is the month just before the event, which serves as the reference period. Each event features only observations for the month right before landfall and for the third/sixth month after the event, $j = 3, 6$. This makes up the three quarterly observations for employment growth during each event. I(Loss>Med) is a treatment indicator for counties with above-median loss, where the median is calculated based on the entire sample. α_{cie} is a county-by-industry-by-event fixed effect and γ_{iste} is a industry-by-state-by-month-by-event fixed effect.

The coefficients of interest β_3 and β_6 represent the treatment difference in employment growth during the first and second quarter relative to the omitted group of counties with below-median loss during the same event in the same state. These are identified via a first-difference in means since only counties with positive loss are included in the sample, and I cannot independently estimate the coefficient for I(Loss<Med).

I address the underlying heterogeneity between treated and control counties on the basis of risk and economic development by interacting the γ_{iste} fixed effect with indicators for risk and income categories. This implies that β_3 and β_6 are identified by comparing industry outcomes only across counties in the same risk/income group in the given state.

Finally, all regressions are weighted by the county employment for each industry six months prior to the beginning of the event. This limits the importance of observations at small counties/sectors, which may not be reported with great accuracy due to the BLS censoring practices and which may not represent the most likely impact at the average county.[16]

Estimation Results

Baseline Results: The estimates in Table 4 reveal that employment at the average industry is 0.48% lower in the first quarter after the disaster and the decline is not made up by faster growth during the second quarter. This is consistent with the difference in labor outcomes from the summary statistics in Table 1, which showed that average decline for low-impact areas is 0.2% versus 0.7% for high-impact areas. This result is surprisingly close to Strobl (2011) which finds a 0.45% decrease in county output growth.[17] Limiting the comparison group to counties with the same risk quartile (column 2) or the same income tercile (column 3) reduces the impact to 0.37%/0.38%, respectively. When counties are grouped by both income and risk, the estimated coefficient suggests that employment falls by 0.33%, with no recovery through the second quarter. The results suggest that comparing counties with different levels of risk and economic development – as is common in the literature – will overestimate the employment impact of natural disasters.

Differences by County Risk: In Table A2, I examine the difference in employment impact by weather risk. Job growth declines primarily in high-risk counties at a rate of 0.53%. The coefficients for each sample, plotted in Figure 2, indicate that in below-median risk counties, employment declines modestly and the estimates is not statistically significant. Table A3 in the appendix is consistent with this finding, showing that average growth in low-risk counties declines form 0.4% to 0.2%, whereas in high-risk counties growth changes from 1.1% to 0%. One explanation is that low-risk places have lower average loss even when it is above-median.

[16] To preserve anonymity, BLS does not report employment in cases where jobs for specific firms can be identifies.

[17] The paper estimates an annual impact for the period of 1970-2005. My results suggest that much of this occurs in the first quarter.

This is supported by Table A3: average loss is 0.1% at low risk and 0.7% at high-risk counties. Alternatively, since high-risk areas provide amenities which attract population inflows and generate high growth, a disaster landfall can halt this expansion, at least in the short run, leading to a substantial growth reduction.

Differences by County Income: The coefficients for each sample divided by the GDP tercile are plotted in the middle panel of Figure 2. They suggest that the majority of the impact is concentrated in the higher-income bracket. While the middle/lower-income estimates are negative, they are not statistically significant. This finding is consistent with Strobl (2011), which finds that higher-income population is more likely to leave.

Differences by Industry: The estimates based on equation 1, where each industry effect is estimated separately, are plotted in the bottom panel of Figure 2. The industries that see a significant decline in employment are: Information, Leisure and Hospitality, Other Services, Trade, Transportation and Utilities. These findings echo the literature on the impact of natural hazards, which highlight that businesses that rely on a store-front and customer foot traffic tend to be mostly impacted by losses (Meltzer et al., 2021).

Monthly Impact: In Table A4 I provide estimates for the monthly impact of landfall and in Figure A1 I plot the event study estimates for the overall impact and by county risk. Monthly growth declines for two consecutive months after the impact for the full sample. For the high-risk counties there is evidence of a prolonged decline with strong impact in the first month and a continued declines in months 3-6.

5 Local Lenders and Employment Recovery

Access to credit is key for a quick recovery, as argued by Noy (2009) and Keerthiratne and Tol (2017). Firms will likely face additional costs after a landfall in order to replace capital, retain employees, access suppliers, and limit down-time.[18] This is a financial challenge when revenue is disrupted and often forces firms to rely on credit or savings in order to restore

[18] This is termed as fixed cost of re-entry in Basker and Miranda (2018).

operations. Consistent with this, Collier et al. (2020) finds that about 40% of firms affected by hurricane Sandy took on additional debt. Residents will also increase demand for credit in order to repair and rebuild homes. Evidence for this is provided by Del Ninno et al. (2003) and Cortés and Strahan (2017).

The landfall of natural disasters can compromise the availability of credit by local lenders who are best positioned to serve the local community. This suggest that the local banking structure can be a key factor during the recovery period. Here, I focus on the difference in the employment dynamics across markets with different prevalence of local lenders, in order to examine whether they can limit the consequences of the negative disaster shock. In the next section, I focus on the impact on bank performance and lending after the landfall.

Expected Effect of Access to Local Lenders

Severe weather can disrupt the provision of credit for two distinct reasons. First, damage to firm capital reduces collateral available to secure credit and makes borrowers more risky, since they can be more likely to default. Consistent with this Berg and Schrader (2012) shows that there was a significant reduction in the probability of loan approval after volcanic activity. Second, reduction in bank capital due to increased defaults on existing loans can limit lender's ability to supply credit (Schwert, 2018).[19] Since local lenders are more likely to experience portfolio deterioration due to their geographic concentration, the key question is whether they can leverage their local specialization and provide more credit than non-local lenders despite the likely more sizable portfolio impairment.

There is already evidence that banks in areas with more severe damages are likely to experience significant loan impairment, which can lead to a reduction in overall lending capacity (Hosono et al., 2016; Schüwer et al., 2019), especially for lenders which lack access to geographically diversified markets (Neely and Wheelock, 1997). Therefore, markets with higher prevalence of small-bank credit can be subject to higher supply disruptions and worse

[19] Instead of business loans, banks can focus on other low-risk assets (Schüwer et al., 2019).

employment outcomes. At the same time, local lenders have a market-specific information advantage related to all firms in a specific market (Paravisini et al., 2015), or have gathered firm-specific information in their role a relationship lender (Bolton et al., 2016).[20] This suggests that they can provide more credit than non-local lenders during the period of lower collateral values, improving the recovery of the local economy.[21]

Are Local Lenders Randomly Assigned?

The local banking structure is unlikely to be independent from the characteristics of the local economy, including the inherent risk of losses from disasters. For example, if only national chains are able to survive substantial losses from disasters – as argued in Basker and Miranda (2018), and these enterprises rely on large lenders, then the risk of losses can reshape both the local economy and the prevalence of local lenders. Similarly, high-income areas can attract national banks and change the local banking industry structure. In these cases, a simple comparison between counties with low and high local finance does not cleanly identify the role of local lenders because these counties will have different disaster risk, income, and industrial structure, among others.

Table 5 helps highlight the difference between counties with different level of local finance. Areas with high local finance tend to have slightly higher risk of losses and experience high-impact events more ofter. They also tend to have lower population and lower income. Almost half of the low-local-finance counties are in the top tercile of income versus close to a third for the high-local-finance ones. I account for these differences in my empirical design by comparing the impact of local lenders across markets with the same income and risk level.

[20]For example, De Jonghe et al. (2020) shows that firms borrowing form banks specializing in a specific market had lower credit disruptions during the 2009 credit crunch. This suggests that markets where smaller lenders play a dominant role can be less impacted by the reduction in collateral values and the increase in uncertainty after landfall.

[21]The tradeoff between the economies of scale from geographically diversified portfolio and dis-economies of scale which weaken the monitoring incentives and limits the ability to process soft information makes the impact of local lenders empirically ambiguous. This tradeoff has been extensively examined in the literature on the benefits of bank diversification. For example, see Acharya et al. (2006) and Tabak et al. (2011). Local lenders may not be affected by the worsening of asymmetric information but may have limited capacity to expand supply if the quality of the existing portfolio suffers.

Empirical Methodology

The empirical analysis is based on the following extension of equation 1 from the previous section:

$$
\begin{aligned}
\Delta \ln \mathrm{Emp}_{cite} = & \sum_{j=\{3,6\}} \beta_j \mathrm{I(t{=}j)} \times \mathrm{I(Loss{>}Med)}_{ce} \\
& + \sum_{j=\{3,6\}} \beta^h_j \mathrm{I(t{=}j)} \times \mathrm{I(Loss{>}Med)}_{ce} \times \mathrm{I(High\ Local\ Finance)}_{ce} \\
& + \sum_{j=\{3,6\}} \sigma^h_j \mathrm{I(t{=}j)} \times \mathrm{I(High\ Local\ Finance)}_{ce} \\
& + \alpha_{cie} + \gamma_{iste} + \epsilon_{cite}
\end{aligned} \tag{2}
$$

The equation introduces interactions with I(High Local Finance) which is an indicator for counties with above-median share of local deposits. The rest of the variable definitions follow from the previous section.

The coefficients of interest β^h_3 and β^h_6 reflect the difference in employment growth for treated counties with higher access to local finance relative to those with low access. They are identified within a (dynamic) difference-in-difference setting which examines whether the employment growth differs between treated and non-treated counties and between those with and without high local finance, after controlling for county-industry-event and industry-state-time-event fixed effects.

A key identification concern is that the banking structure can be correlated with the economic development of the county, which, in turn, can depend on the level of risk of severe weather. This concern is supported by the sample. In Table 5, I already highlighted some key differences by income and risk emerging when areas are split according to local finance. In order to limit the underlying heterogeneity within the comparison groups I follow the methodology in the previous section, which restricts the control groups to those with the same risk and income level. The effectiveness of this approach is evident in Table A6 in the appendix, which compares only places with high income and risk. In this case variation in the banking structure does not influence the average damage, the proportion of treatment, the income level, and population. This ensures that the difference-in-difference comparison between treated counties with low and high local finance is not confounded by other underlying differences.[22]

Estimation Results

Baseline Results: The estimates in Table 6 broadly suggest that the reduction in job growth occurs primarily in counties with higher share of local deposits. Based on the specification that includes time-by-industry-by-state fixed effects (column 1), treatment is associated with a 0.2% reduction in growth in the first quarter at low-local-finance counties and an additional 0.68% reduction at high local finance counties. This effect dissipates in the second quarter with low finance, while it remains persistent for high finance counties – growth declines again by 0.65%. The results also indicate that high finance counties with below-median impact grow 0.24% faster than those with low local finance.

Adjusting the comparison groups in columns (2)-(4) reduces the growth impact of natural hazards across the board, as the control and treatment groups become more similar. The effect of treatment at low-local-finance counties loses statistical significance and ranges from 0.05% to 0.17%. The additional first quarter reduction at high-local-finance counties remains statistically significant, ranging from 0.5% to 0.62%. The results suggest that higher prevalence of local lenders is associated with worse employment outcomes following a significant loss event. Because the empirical design assures that relative damage, income, and risk fall within the same category, the poor employment performance with high local finance is unlikely to be caused by a stronger shock or differences in local development.

Differences by County Risk: The top row of Figure 3 compares the effect of local finance by severe-weather risk. Employment growth in the first quarter is the same in counties with below-median risk regardless of the prevalence of local finance. Across counties with above-

[22]More generally, the inclusion of the two sets of fixed effects accounts for invariant differences in county-industry growth and time-varying demand shocks affecting each industry across counties in the same group.

median risk – where I have controlled for income differences and damages are expected to be similar – higher prevalence of local finance is associated with worse recovery. This can be due to the higher damages that are likely in these counties. In such cases, access to national geographically-diversified lenders can improve the recovery of the local economy. It can also be the case that local lenders possess better local information and pull away because they update their expectations about future risk. Here, I cannot distinguish between the two hypotheses but I explore this at length in the next section.

Differences by County Income: The second row of Figure 3 examines differences in the impact of local finance by county income. The evidence suggests that high- and middle-income counties experience worse reduction in job growth without access to national lenders following a disaster. Lower income counties are more likely to receive relief grants after disasters and do not need to rely on financial intermediation in order to recover. In contrast, higher income counties that are more reliant on private credit fare worse when the local banking structure is dominated by smaller, un-diversified lenders.

Differences by Industry: The bottom row of Figure 3 compares the industry-specific impact of treatment depending on the prevalence of local finance. This analysis helps uncover which industries benefit from access to national lenders following a severe disaster and which can benefit from local lenders. Firms in the Leisure and Hospitality, and Trade, Transportation, and Utilities industries recover within the first quarter after a disaster in counties where national lenders are more prevalent. In contrast, such firms tend to experience a pronounced reduction in employment growth when local lenders are more prevalent. Sectors which rely on local foot traffic and discretionary spending are at a higher risk of failure after losses from severe weather (Guimaraes et al., 1993; Belasen and Polachek, 2008; Meltzer et al., 2021). This can make lending to such enterprises particularly undesirable for lenders looking to limit exposure to defaults after a disaster. Landfalls represent a systemic event for geographically un-diversified lenders and can worsen the quality of their portfolio. Faced with a potential increase in defaults on existing loans, such lenders limit risk by reducing credit to risky sectors during the period when demand from such businesses can increase. Lenders without systemic exposure to disasters do not need to limit risk and can provide additional credit to these industries, which results in a minimal reduction in employment growth.

Monthly Impact: Table A7 in the appendix lists the estimates from the monthly event study, for the full sample and by county risk. For the full sample, counties with higher prevalence of local finance have 0.32% decline in employment growth in the month after landfall, followed by a 0.22% decline, and another 0.15% decline in the fourth month. Counties with higher access to diversified lenders decline by 0.13% only in the month after. Figure A2 plots these coefficients by county risk. High local finance counties experience a persistent recession for up to four months after the disaster primarily in areas with high risk.

All together, the evidence consistently shows that local finance exacerbates disaster-driven job contractions. The difference in the recovery dynamics across areas with varying prevalence of local lenders is most evident in counties with higher risk – where overall damage is higher, with higher income – where the local population may rely more on private credit, and with more risky industry sectors – where local lenders can suffer higher loan losses. My results are consistent with micro evidence focusing on the ability of multi-market banks to allocate funding to areas with high demand (Cortés and Strahan, 2017; Koetter et al., 2019).

6 Why Community Banks Affect the Recovery?

The employment evidence suggests that counties with more local lenders do worse. Without evidence about lending activity and portfolio condition, it is not clear exactly why this occurs and whether local lenders play a key role for this outcome. From a theoretical perspective single-market lenders can have an ambiguous impact on local economic conditions following a disaster (Keeton et al., 2009). The reason why they can amplify negative shocks is that they experience portfolio losses which disproportionately reduce their credit supply. Alternatively, even with limited losses, they may not have the necessary liquidity to expand credit as much as bigger and more diversified lenders.[23] Finally, local lenders may possess better information about local businesses (Acharya et al., 2006; Hayden et al., 2007; Tabak et al., 2011) and deny credit after the disasters to businesses that would no survive, while non-local lenders continue to support such enterprises.[24]

In this section, I focus on the following questions to highlight the channel through which local and non-local lenders affect the recovery. First, to what extent do local lenders experience a deterioration of their loan portfolio after the disaster? Second, how do they adjust their capital levels in response to the potential increase in uncertainty after the landfall? Third, how does local and non-local bank lending respond to the impact?

Empirical Methodology

I pursue two approaches, using bank observations from a sample of all commercial banks, and by focusing only on local banks – with over 66% of deposits located in one county.

All Lenders

In the sample of all lenders, I measure exposure to natural disasters using the one-year lagged share of deposits in each county as weights. I calculate the proportion of deposits located in counties with positive damage and in those with above-median (severe) loss. I define four mutually exclusive groups based on these shares:

1. control A: 0% to 66% in areas with positive loss & 0% with severe loss;
2. treatment A: 66% to 100% in areas with positive loss & 0% with severe loss;
3. treatment B: 66% to 100% in areas with positive loss & 1% to 66% with severe loss;
4. treatment C: 66% to 100% in areas with positive loss & 66% to 100% with severe loss;

[23] In contrast, local lenders can improve the recovery if they have superior local information due to their market specialization and proximity, which allows them to extend more credit than non-local lenders, despite their systemic exposure to the disaster.

[24] In other words, local lenders may improve efficient exit (Basker and Miranda, 2018)..

The control group of lenders has a minimal exposure to disasters, with at most 66% of deposits in counties with mild loss. The treatment groups A, B, and C include lenders with the majority of deposits in counties with some loss from disasters. The three groups differ by their exposure to severe losses – from none in A to over 66% in C. I refer to these groups as No/Medium/High exposure lenders in the regression model below.

With these definitions I estimate the following specification:

$$\begin{aligned} Y_{bt} = & \sum_{e,j=\{3,6\}} \beta_j^h \mathrm{I(t{=}j)} \times \mathrm{I(High\ Exposure\ to\ Loss{>}Med)}_{be} \\ & + \sum_{e,j=\{3,6\}} \beta_j^m \mathrm{I(t{=}j)} \times \mathrm{I(Medium\ Exposure\ to\ Loss{>}Med)}_{be} \\ & + \sum_{e,j=\{3,6\}} \beta_j^l \mathrm{I(t{=}j)} \times \mathrm{I(No\ Exposure\ to\ Loss{>}Med)}_{be} \\ & + \gamma Z_{bt} + \alpha_b + \gamma_t + \epsilon_{bt} \end{aligned} \tag{3}$$

where Y_{bt} stands for a performance or lending measure for bank b, during quarter closest to month t. Note that since one bank can be exposed to several events in different states at the same time, I can no longer distinguish separate events. Because of this, equation 3 simplifies notation slightly by dropping the additional summation across all events that the lender can be exposed to during a given quarter.

I(High Exposure to Loss>Med) is an indicator for treatment group C as defined above. Lenders in this group are systemically impacted by disasters since the majority of their deposits are located in severe-loss counties. I(Medium Exposure to Loss>Med) stands for treatment group B, which has intermediate exposure to severe-loss counties, with the majority of its deposits located in counties with mild loss. I(No Exposure to Loss>Med) reflects treatment group A, which has the lowest exposure to disasters, with the majority of its deposits in counties with mild loss and none in areas with severe damage. Control group A is omitted.

Z_{bt} includes the four-quarter lags of the following bank variables: log of assets, deposits/assets, securities/assets, loans/assets, tier 1 capital ratio, real estate loans/loans, and roe. The coefficient estimates for these variables are suppressed in the main results.

This specification does not allow location-specific fixed effects because lenders operate in multiple location. It includes a time fixed effect, γ_t, which controls for period shocks common to all lenders and a bank fixed effects to account for bank differences. I include as additional controls the proportion of deposits located in each GDP and Risk category.

Finally, I focus on the quarter before the impact and the two quarters after. Bank observations are released each quarter in the Call reports and I match the most recent quarter before the month of the disaster as a pre-quarter, and the two most recent quarters after as post-quarters.

The β coefficients are of interest in this specification. β_j^h reflects the difference in bank outcomes for lenders with high exposure to above-median disasters relative to those with no exposure. These lenders are subject to a systemic impact from the landfall and a possible deterioration in the portfolio quality. β_j^m reflects the difference in outcomes for lenders which can be considered non-local with respect to counties with severe loss and are expected to be subject to lower impact from the landfall in terms of portfolio risk. β_j^l captures the difference for lenders with no exposure to above-median-loss counties but with majority of deposits in counties with below-median loss. It reflects how systemic exposure to low-damage events affects lenders. Note that banks can lend at a distance and experience loan losses even if they are not physically located in areas with above-median damage, as in Koetter et al. (2019). This is the reason for distinguishing this group of no-exposure banks from the control group.

Local Lenders

Focusing only on local lenders – each of which is allocated to one county – allows me to preserve the setting from the employment specifications. More specifically, each lender can be located in a control or treatment county and in a county with above- or below-median share of local deposits. With these definitions I estimate the following specification:

$$
\begin{aligned}
Y_{bcte} = & \sum_{j=\{3,6\}} \beta_j^h \mathrm{I(t{=}j)} \times \mathrm{I(Loss{>}Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce} \\
& + \sum_{j=\{3,6\}} \beta_j^l \mathrm{I(t{=}j)} \times \mathrm{I(Loss{>}Med)}_{ce} \times \mathrm{I(Non\text{-}Local\ Finance)}_{ce} \\
& + \sum_{j=\{3,6\}} \sigma_j^h \mathrm{I(t{=}j)} \times \mathrm{I(Loss{<}Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce} \\
& + \gamma Z_{bte} + \alpha_{bce} + \gamma_{ste} + \epsilon_{bcte}
\end{aligned} \tag{4}
$$

where Y_{bcte} is a performance or lending measure for bank b, in county c, at time t, during event e. $\mathrm{I(Loss{>}Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce}$ is an indicator for whether the lender is located in a county with above-median loss which also has above-median share of local deposits. $\mathrm{I(Loss{>}Med)}_{ce} \times \mathrm{I(Non\text{-}Local\ Finance)}_{ce}$ is an indicator for a lender in a high-impact county where the share of local deposits is below the median. $\mathrm{I(Loss{<}Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce}$ is an indicator for a local lender residing in a county with below-median loss where local finance is more prevalent. The omitted group includes lenders in counties with below-median impact where local finance is not prevalent.

I control for invariant bank differences during each event with α_{bce}. Similar to the employment specification, I also control for common quarter-specific shocks to all lenders located in the same state during event e. To further limit any underlying heterogeneity in the risk and income of different counties, I interact this fixed effect with the county income and risk category. Since lenders can self-select into markets depending on the local level of development or the risk from natural hazard, this control makes sure that only lenders in markets with the same characteristics are used as control groups.

The coefficients of interest β^h and β^l reflect whether local lenders in counties with above-median loss differ in lending or portfolio performance compared to banks in counties with limited damage and whether this depends on the prevalence of local finance. Since local lenders in general may be more systemically impacted by natural hazards with above-median loss, the difference between β^h and β^l may be minimal. It is also possible that counties with lower prevalence of local finance may benefit from the additional credit capacity of non-local lenders, which can limit the deterioration in the local economy. Therefore, the impact on local lenders may differ depending on the share of local deposits.

Estimation Results

All Lenders

The estimates of equation 3 for the full sample are listed in Table 7. There is evidence that substantial bank exposure to severe disasters is associated with additional losses from loan defaults. Estimates in column (2) suggest that charge-offs are about 2 basis points (bp) higher for all lenders with a significant proportion of deposits in counties affected by disasters, compared to banks with limited disaster exposure.[25] According to Table 3, this increase represents about 20% of charge-offs for the average bank.[26] Dividing the sample by local and non-local lenders, in Table 8, shows that the increase is only statistically significant for local lenders. Non-local lenders are not subject to similar losses with exposure to severe events. Dividing the sample based on whether lenders mostly serve low- or high-local-finance counties, in Table 9, suggests that losses are expected regardless of the prevalence of local finance. Overall, defaults increase with exposure to severe events, predominantly for lenders with higher local concentration, independently of the level of access to local finance.

Even without direct losses, lenders can experience an increase in risk among the pool of existing or future borrowers. This may require an increase in the amount of bank capital or a reduction in overall lending, in order to stabilize their capital ratio. Columns (3) and (4) in Table 7 focus on the capital ratio. The results in column (3) indicate that lenders with high exposure to counties with severe loss increase capital ratios by about 7 bp, which represents a somewhat modest amount for the average lender in the sample with 16% tier 1

[25] The only exception are banks with with intermediate exposure to high-loss counties, where the coefficient estimate is 1.4bp but is not statistically significant.

[26] Note that charge-offs are calculated as a fraction of four-quarter lag of loans in order to limit the impact of current change in lending on the ratio.

capital ratio. The coefficient is reduced to 6 bp in column (4) and becomes not statistically significant. Table 8 indicates that the increase is most pronounced for non-local lenders, which increase capital ratios by about 0.1%. This suggests that lenders which avoid direct losses and do not increases charge-offs may be subject to increased risk of defaults. Table 9 implies that this risk is most prevalent for lenders which mostly serve high-local-finance counties. All together, the evidence indicates that high disaster exposure can either increase defaults at mostly local lenders or cause non-local lenders to raise capital in order to prepare for a potential increase in defaults – mostly in markets where local banks play a dominant role. In either case, high exposure can increase costs for affected banks and limit their ability to provide additional credit.

In columns (5)-(6) of Table 7, I find that banks with high disaster exposure do not increase lending during the recovery period, when demand is expected to be elevated.[27] In contrast, lenders with medium exposure increase credit by about 1.5%. Table 8 confirms that the increase is most prevalent among non-local lenders, which originate 2% more credit. Importantly, Table 9 indicates that this expansion centers on markets with low prevalence of local finance. This finding is consistent with the evidence in the previous section that counties with lower prevalence of local lenders outperform those with higher local finance. The results here suggest that non-local lenders with medium exposure to severe disasters are key drivers of recovery. They have lower charge-offs, do not focus on increasing capital as much as those with higher exposure, and ultimately are able to expand lending.[28]

Local Lenders

The estimates of equation 4 are listed in Table 10. By focusing only on local lenders that operate primarily in one home county I can provide more concrete evidence about the lending dynamic in disaster counties. The overall evidence is complementary to the results from the universe of lenders, suggesting that un-diversified lenders in high-impact counties

[27] Similarly, banks with minimal exposure do not adjust overall credit in the post period.

[28] Since this sample does not allow me to locate exactly where banks increase credit, I cannot be certain that lenders with medium exposure increase credit specifically in areas with lower prevalence of local finance.

experience significant losses due to higher charge-offs and do not increase originations during the post period. In fact, I find that local lenders reduce credit across the board.

The evidence in column (1) suggests that charge-offs at local lenders are 3.3 bp higher during the first quarter in counties with above-median loss, compared to local lenders operating in counties with lower damage. This represent about a third of charge-offs for the average lender. According to column (2), these are particularly pronounced in counties with above-median loss and a higher prevalence of local lenders. They are persistently higher in these areas even in the second quarter after landfall. Charge-offs do not increase similarly for local lenders in counties with below-median loss. Overall, local lenders appear particularly vulnerable to severe disasters, which can generate significant losses for their portfolio of existing borrowers.

Evidence related to the capital ratio in columns (3) and (4) is not conclusive because estimates are not statistically significant. This is consistent with the results above, which suggest that mostly non-local lenders with high disaster exposure increase capital ratios. Local lenders are more likely to experience direct losses in which case increasing capital ratios may be challenging.

Finally, the results in columns (5) and (6) focus on total lending. They strongly indicate that local lenders reduce originations in both quarters following disasters with severe damage. Credit declines between 5% and 7.1% according to column (5). In column (6), contractions are prevalent across all local lenders with somewhat stronger declines in counties with above-median loss, where lending falls between 0.85% to 1.35%.

This evidence is consistent and complementary with the results from the sample of all banks. In that case, I find that lenders with a limited fraction of deposits in counties with above-median loss, i.e. non-local lenders with respect to high-impact counties, expand lending faster than the rest. Here, I find that local lenders residing in high-impact counties reduce originations more than local lenders elsewhere.

Discussion

All together, the evidence from both samples suggests that counties with lower prevalence of local lenders have higher credit originations after severe losses from disasters, while areas where local lenders are more common see limited changes in credit. Somewhat surprisingly, I find that un-diversified local lenders with exposure to both high- and low-impact disasters generally reduce lending. Since this reduction is accompanied by higher losses in the loan portfolio, it is likely that local lenders focus on rebuilding capital and managing risk rather than on expanding credit. In contrast, I find that diversified non-local banks which are not subject to significant losses or higher default risk increase lending post disaster.

The results complement the employment findings in the previous section and provide additional context for why local finance hampers the recovery in counties with above-median losses. Local lenders appear to suffer substantial losses from the systemic exposure to disasters through the increase in risk or actual defaults. Perhaps, because of the increase in costs associated with higher risk, lenders serving high-impact counties do not increase credit. This behavior is consistent with the reduction in employment in high-impact counties, where higher credit demand for rebuilding is met with lower credit supply.

7 Robustness

Level of Concentration of Local Banks

In this section, I examine the stability of the baseline results to more restrictive definition of access to local finance. I focus on alternative classifications of local lenders based on different proportions of a bank's deposits in one county. Increasing the proportion of deposits in one county will further limit the extent of variation in the data by reducing the fraction of local deposits in affected counties, while potentially mis-classifying some counties as having no access to local finance. Table 11 lists the estimates from this sensitivity analysis. As more local lenders are classified as non-local, counties where local finance is less prevalent will also experience declines in employment, making the difference due to local finance less pronounced. In column (4), where only one-county lenders are considered as local, there is no difference in employment outcomes by local finance prevalence.

Block-buster Hurricanes

Table 12 lists estimates for four of the most destructive hurricanes in the US history during the sample period. These include: Katrina with $125B, Harvey with $125B, Sandy with $69B, and Ike with $38B in losses (Weinkle et al., 2018). The negative effect of access to local finance is evident in three of the last four most destructive events. This is consistent with the interpretation that high-impact events overwhelm local lenders by increasing costs due to higher (risk from) defaults. Local lenders offset this increase in losses by reducing new credit, which appears to be detrimental for the local economy.

Alternative Measures of Access to Local Finance

In Table 11, I also examine the case when all lenders with less than $1B in assets are assumed to be local. Column (5) shows that defining local finance on the basis of asset size does not lead to different employment outcomes. This suggests that what matters here is not the size but the concentration of lenders.

8 Conclusion

Can non-diversified lenders improve local economic resilience or do they amplify the negative shock? The evidence, which is based on a difference-in-difference model of 3-month industry jobs growth in counties with losses, consistently shows that access to local finance amplifies the employment contractions. This applies to the average industry in affected counties, to counties with higher risk, to sectors that rely on foot traffic or discretionary spending, and has a particularly strong effect on higher-income areas. The evidence is based on novel data about the natural hazard losses in US coastal states during 1998-2019. It account for the likelihood of weather-related damages (weather risk) using learning algorithm predictions, based on extensive set of variables reflecting the vulnerability of residents to natural hazards and the frequency of severe weather.

How important are portfolio losses and borrower risk after landfall? The evidence from two different regression models suggests that non-diversified local lenders with exposure to high-impact disasters reduce lending. Importantly, this reduction is accompanied by higher losses in the loan portfolio, indicating that local lenders focus on rebuilding capital and managing risk rather than on expanding credit. In contrast, diversified, non-local banks which are not subject to significant losses or higher default risk increase lending post disaster, which can explain why counties with more non-local lenders have faster employment growth.

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Tables and Figures

Table 1: Summary Statistics by Disaster Impact

The table list selected summary statistics for the sample of county-industry observations that include the quarter before and two quarters after all of the included disaster events. The first column covers all observations; columns 3 and 4 are divided relative to the sample median county loss – low impact is below the median, while high impact is above. Damage is total county loss during a disaster, scaled by county total income in the previous year. Low/High Risk is based on the predicted damage from the learning algorithm described in the data section. Low/High risk counties have expected loss below/above the state median. Employment growth refers to the 3-month jobs growth across all industries included in the sample. Pre Q1 refers to the three month preceding a disaster, while post Q1-Q2 refers to the next six months. Low/High Local Finance is based on the state median of the share of local deposits at each county: areas below the median are low, areas above are high. GDP tercile divides the counties into three categories based on the state income distribution for the entire sample.

		Impact Level	
Variable	**Overall**, N = 96,332	**I, Low**, N = 49,383	**II, High**, N = 46,949
Damage (% GDP)	0.5 (1.4) [0.0, 0.3]	0.2 (0.8) [0.0, 0.0]	0.8 (1.7) [0.1, 0.7]
Risk Level			
I, Low	43,968 (46%)	26,778 (54%)	17,190 (37%)
II, High	52,364 (54%)	22,605 (46%)	29,759 (63%)
Employment Growth (%)	0.4 (13.7) [-2.8, 2.8]	0.5 (14.1) [-2.7, 2.8]	0.3 (13.3) [-2.9, 2.9]
Employment Gr: Pre Q1	0.7 (12.7) [-2.3, 3.0]	0.6 (11.2) [-2.2, 2.9]	0.8 (14.1) [-2.4, 3.1]
Employment Gr: Post Q1-Q2	0.2 (14.2) [-3.1, 2.7]	0.4 (15.3) [-3.0, 2.7]	0.1 (13.0) [-3.2, 2.8]
Personal Income ($B)	9 (19) [1, 7]	10 (19) [1, 9]	7 (18) [1, 5]
Population (10k)	21 (40) [3, 20]	24 (41) [4, 25]	18 (40) [3, 14]
Share of local Deposits (%)	24 (25) [1, 40]	24 (24) [2, 40]	25 (25) [0, 40]
Local Finance			
I, Low	50,605 (53%)	26,535 (54%)	24,070 (51%)
II, High	45,727 (47%)	22,848 (46%)	22,879 (49%)
GDP Tertile			
GDP I (L)	22,565 (23%)	9,937 (20%)	12,628 (27%)
GDP II (M)	34,088 (35%)	16,368 (33%)	17,720 (38%)
GDP III (H)	39,679 (41%)	23,078 (47%)	16,601 (35%)

[1] Mean (SD) [IQR]; n (%)

Table 2: Industry Summary Statistics by Impact

The table lists employment growth for all industries in the sample divided by the level of impact – low impact is below the median, while high impact is above. Pre refers to the 3-month growth during the quarter immediately preceding the disaster landfall, while post refers to the the average 3-month growth for the two quarters after the impact. All growth numbers represent percentages.

	Impact Level	
Variable	**I, Low**, N = 49,383	**II, High**, N = 46,949
Construction –Emp Gr: Pre	2 (15)	2 (12)
Construction –Emp Gr: Post	0 (18)	0 (11)
Education and Health Services –Emp Gr: Pre	-0.2 (5.4)	0.0 (5.0)
Education and Health Services –Emp Gr: Post	0.6 (9.2)	0.8 (6.5)
Financial Activities –Emp Gr: Pre	0.6 (7.3)	0.6 (5.7)
Financial Activities –Emp Gr: Post	-0.1 (6.2)	-0.2 (10.7)
Information –Emp Gr: Pre	0.0 (7.9)	-0.2 (9.1)
Information –Emp Gr: Post	0.7 (15.0)	-0.2 (11.3)
Leisure and Hospitality –Emp Gr: Pre	2 (12)	2 (12)
Leisure and Hospitality –Emp Gr: Post	0 (14)	-1 (14)
Manufacturing –Emp Gr: Pre	0.3 (9.8)	0.2 (9.0)
Manufacturing –Emp Gr: Post	0.4 (14.3)	-0.3 (10.5)
Natural Resources and Mining –Emp Gr: Pre	0 (22)	1 (39)
Natural Resources and Mining –Emp Gr: Post	2 (34)	1 (26)
Other Services –Emp Gr: Pre	0.5 (6.9)	0.7 (7.3)
Other Services –Emp Gr: Post	-0.3 (7.9)	-0.1 (12.9)
Professional and Business Services –Emp Gr: Pre	1 (9)	1 (9)
Professional and Business Services –Emp Gr: Post	1 (11)	1 (12)
Trade, Transportation, and Utilities –Emp Gr: Pre	0.1 (4.4)	-0.1 (4.8)
Trade, Transportation, and Utilities –Emp Gr: Post	0.2 (7.1)	0.1 (5.2)

[1] Mean (SD)

Table 3: Bank Summary Statistics by Exposure

The table list selected summary statistics for the quarterly observations in the sample of all lenders. The sample includes only the observations for the quarter before and two quarters after the occurrence of any disaster in the sample. The first column features all observations, while columns 2-5 list observations based on bank exposure to disasters, as follows. 0 refers to observations during disasters for banks without any deposits in affected counties. I (L) refers to observations for lenders with 66% to 100% in areas with positive loss & 0% with above-median (severe) loss; II (M) refers to lenders with 66% to 100% in areas with positive loss & 1% to 66% with severe loss; III (H) refer to lenders with 66% to 100% in areas with positive loss & 66% to 100% with severe loss. High Loc Finance (%) refers to the fraction of bank deposits located in counties with above-median fraction of local deposits. GDP (%) and Risk (%) refers to the percentage of deposits located in counties designated to the corresponding GDP and weather Risk category.

		Exposure Level			
Variable	**Overall**, N = 38,426	**0**, N = 22,333	**I, (L)**, N = 6,788	**II, (M)**, N = 1,551	**III, (H)**, N = 7,754
Log Asset	13 (2) [12, 14]	13 (2) [12, 14]	12 (1) [12, 13]	13 (1) [12, 14]	12 (1) [11, 13]
Log Loans	13 (2) [11, 13]	13 (2) [12, 14]	12 (1) [11, 12]	13 (1) [12, 13]	12 (1) [11, 12]
Charge-offs/Loans (%)	0.1 (0.3) [0.0, 0.1]	0.1 (0.3) [0.0, 0.1]	0.1 (0.3) [0.0, 0.1]	0.1 (0.2) [0.0, 0.1]	0.1 (0.3) [0.0, 0.1]
Deposits/Asset (%)	84 (23) [79, 89]	83 (13) [78, 89]	85 (49) [80, 90]	83 (11) [77, 89]	85 (9) [81, 90]
Securities/Asset (%)	22 (14) [11, 29]	21 (13) [12, 29]	22 (15) [11, 30]	21 (13) [12, 28]	23 (14) [11, 31]
Loans/Asset (%)	66 (20) [56, 76]	66 (17) [57, 76]	66 (33) [56, 77]	67 (13) [59, 77]	64 (16) [54, 76]
Tier1 Ratio (%)	16 (7) [12, 18]	16 (6) [12, 18]	17 (7) [13, 20]	15 (5) [12, 17]	18 (7) [13, 20]
RE Loans/Loans (%)	79 (25) [69, 91]	77 (21) [67, 90]	82 (41) [73, 95]	80 (16) [72, 91]	79 (18) [69, 91]
ROE (%)	8 (10) [5, 13]	8 (10) [5, 13]	7 (10) [4, 12]	9 (8) [5, 13]	8 (10) [4, 12]
High Loc Finance (%)	9,656 (25%)	3,058 (14%)	2,960 (44%)	250 (16%)	3,388 (44%)
Local Banks	16,348 (43%)	5,114 (23%)	5,460 (80%)	345 (22%)	5,429 (70%)
GDP II, (M) (%)	18 (34) [0, 14]	12 (27) [0, 6]	24 (41) [0, 48]	26 (31) [0, 45]	28 (41) [0, 69]
GDP II, (H) (%)	39 (42) [0, 93]	28 (35) [0, 45]	60 (46) [0, 100]	53 (37) [15, 87]	51 (46) [0, 100]
Risk II, (Qrt2) (%)	19 (34) [0, 17]	13 (27) [0, 10]	28 (42) [0, 77]	26 (31) [0, 45]	25 (40) [0, 55]
Risk II, (Qrt3) (%)	16 (32) [0, 8]	11 (25) [0, 4]	19 (37) [0, 0]	17 (28) [0, 24]	27 (40) [0, 68]
Risk II, (Qrt4) (%)	17 (33) [0, 11]	12 (26) [0, 7]	17 (36) [0, 0]	19 (30) [0, 27]	30 (42) [0, 80]

[1] Mean (SD) [IQR]; n (%)

Table 4: Baseline Quarterly Employment Impact of Natural Hazards

The table list estimates from: $\Delta \ln \text{Emp}_{cite} = \sum_{j=\{3,6\}} \beta_j \text{I(t=j)} \times \text{I(Loss>Med)}_{ce} + \alpha_{cie} + \gamma_{iste} + \epsilon_{cite}$, where $\Delta \ln \text{Emp}_{cite}$ is the three-month log-difference in industry i employment in county c during natural hazard e. I(Loss>Med) is a treatment indicator for a counties with above-median loss, where the median is calculated based on the entire sample. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. The fixed effects and standard error clusters use the following abbreviations: c - county, i - industry, e - event, t - month, s - state, gdp - income group, risk - risk group. Risk group is based on the quartile of expected loss within the state. Income group is based on the tercile of county income. The standard-errors row indicates the level of clustering for the standard errors.

	$\Delta \ln Emp$			
	(1)	(2)	(3)	(4)
Loss>Med x Post Q1	-0.0048***	-0.0037***	-0.0038***	-0.0033**
	(0.0013)	(0.0013)	(0.0012)	(0.0013)
Loss>Med x Post Q2	-0.0014	-0.0008	-0.0009	-0.0008
	(0.0013)	(0.0014)	(0.0012)	(0.0014)
Standard-Errors	c-i-e & t-i-s	c-i-e & t-i-s-risk	c-i-e & t-i-s-gdp	c-i-e & t-i-s-risk-gdp
R^2	0.60534	0.70648	0.68356	0.80190
Observations	96,332	96,332	96,332	96,332
c-i-e fixed effects	✓	✓	✓	✓
t-i-s fixed effects	✓			
t-i-s-risk fixed effects		✓		
t-i-s-gdp fixed effects			✓	
t-i-s-risk-gdp fixed effects				✓

Table 5: Summary Statistics by Local Finance

The table list selected summary statistics for the sample of county-industry observations that include the quarter before and two quarters after all of the included disaster events. The first column covers all observations; columns 3 and 4 are divided relative to the state median fraction of local deposits – low is below the median, while high is above. Damage is total county loss during a disaster, scaled by county total income in the previous year. Low/High Risk is based on the predicted damage from the learning algorithm described in the data section. Low/High risk counties have expected loss below/above the state median. Employment growth refers to the 3-month jobs growth across all industries included in the sample. Pre Q1 refers to the three month preceding a disaster, while post Q1-Q2 refers to the next six months. GDP tercile divides the counties into three categories based on the state income distribution for the entire sample.

		Local Finance	
Variable	**Overall**, N = 96,332	**I, Low**, N = 50,605	**II, High**, N = 45,727
Risk Level			
I, Low	43,968 (46%)	23,657 (47%)	20,311 (44%)
II, High	52,364 (54%)	26,948 (53%)	25,416 (56%)
Employment Growth (%)	0.4 (13.7) [-2.8, 2.8]	0.4 (14.6) [-2.7, 2.8]	0.4 (12.8) [-3.0, 2.9]
Employment Gr: Pre Q1	0.7 (12.7) [-2.3, 3.0]	0.8 (13.9) [-2.2, 2.9]	0.6 (11.2) [-2.4, 3.1]
Employment Gr: Post Q1-Q2	0.2 (14.2) [-3.1, 2.7]	0.3 (14.9) [-3.0, 2.7]	0.2 (13.5) [-3.2, 2.8]
Employment Gr:High Impact Pre Q1	0.8 (14.1) [-2.4, 3.1]	0.9 (16.3) [-2.3, 2.9]	0.7 (11.2) [-2.4, 3.3]
Employment Gr:High Impact Post Q1-Q2	0.1 (13.0) [-3.2, 2.8]	0.0 (12.8) [-3.1, 2.7]	0.2 (13.2) [-3.3, 2.8]
Damage (% GDP)	0.5 (1.4) [0.0, 0.3]	0.5 (1.5) [0.0, 0.2]	0.4 (1.3) [0.0, 0.3]
Impact			
I, Low	49,383 (51%)	26,535 (52%)	22,848 (50%)
II, High	46,949 (49%)	24,070 (48%)	22,879 (50%)
Personal Income ($B)	9 (19) [1, 7]	9 (19) [1, 9]	8 (19) [1, 6]
Population (10k)	21 (40) [3, 20]	23 (42) [4, 25]	18 (38) [3, 16]
Share of local Deposits (%)	24 (25) [1, 40]	9 (13) [0, 14]	41 (23) [23, 57]
GDP Tertile			
GDP I (L)	22,565 (23%)	11,220 (22%)	11,345 (25%)
GDP II (M)	34,088 (35%)	16,486 (33%)	17,602 (38%)
GDP III (H)	39,679 (41%)	22,899 (45%)	16,780 (37%)

[1] n (%); Mean (SD) [IQR]

Table 6: Local Finance and Quarterly Employment Impact of Natural Hazards

The table list estimates from: $\Delta \ln \text{Emp}_{cite} = \sum_{j=\{3,6\}} \beta_j \text{I(t=j)} \times \text{I(Loss>Med)}_{ce} + \sum_{j=\{3,6\}} \beta_j^h \text{I(t=j)} \times \text{I(Loss>Med)}_{ce} \times \text{I(High Local Finance)}_{ce} + \sum_{j=\{3,6\}} \sigma_j^h \text{I(t=j)} \times \text{I(High Local Finance)}_{ce} + \alpha_{cie} + \gamma_{iste} + \epsilon_{cite}$ is the three-month log-difference in industry i employment in county c during natural hazard e. I(Loss>Med) is a treatment indicator for a counties with above-median loss, where the median is calculated based on the entire sample. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. The fixed effects and standard error clusters use the following abbreviations: c - county, i - industry, e - event, t - month, s - state, gdp - income group, risk - risk group. Risk group is based on the quartile of expected loss within the state. Income group is based on the tercile of county income. The standard-errors row indicates the level of clustering for the standard errors.

	$\Delta \ln Emp$			
	(1)	(2)	(3)	(4)
Loss>Med x Post Q1 x High Local Fin	-0.0068***	-0.0057**	-0.0050**	-0.0062**
	(0.0021)	(0.0025)	(0.0023)	(0.0027)
Loss>Med x Post Q2 x High Local Fin	-0.0065***	-0.0033	-0.0039*	-0.0030
	(0.0021)	(0.0024)	(0.0022)	(0.0027)
Loss>Med x Post Q1	-0.0020*	-0.0013	-0.0017	-0.0005
	(0.0012)	(0.0015)	(0.0012)	(0.0017)
Loss>Med x Post Q2	0.0014	0.0006	0.0008	0.0005
	(0.0015)	(0.0017)	(0.0013)	(0.0017)
Post Q1 x High Local Fin	0.0024*	0.0005	0.0013	0.0003
	(0.0014)	(0.0016)	(0.0014)	(0.0017)
Post Q2 x High Local Fin	0.0024*	0.0001	0.0007	-0.0001
	(0.0014)	(0.0016)	(0.0015)	(0.0017)
Standard-Errors	c-i-e & t-i-s	c-i-e & t-i-s-risk	c-i-e & t-i-s-gdp	c-i-e & t-i-s-risk-gdp
R^2	0.60362	0.70522	0.68388	0.79938
Observations	95,603	95,603	95,603	95,603
c-i-e fixed effects	✓	✓	✓	✓
t-i-s fixed effects	✓			
t-i-s-risk fixed effects		✓		
t-i-s-gdp fixed effects			✓	
t-i-s-risk-gdp fixed effects				✓

Table 7: Impact of Natural Hazards on Bank Performance and Lending: All Lenders

The table list estimates from: $Y_{bt} = \sum_{j=\{3,6\}} \beta_j^h \text{I(t=j)} \times \text{I(High Exposure to Loss>Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^m \text{I(t=j)} \times \text{I(Medium Exposure to Loss>Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^l \text{I(t=j)} \times \text{I(No Exposure to Loss>Med)}_{be} + \gamma Z_{bt} + \alpha_b + \gamma_t + \epsilon_{bt}$ where Y_{bt} stands for a performance or lending measure for bank b, during quarter closest to month t. I(High Exposure to Loss>Med) is an indicator for lenders with 66% to 100% of deposits in areas with positive loss & 66% to 100% with above-median (severe) loss; I(Medium Exposure to Loss>Med) stands for lenders with 66% to 100% of deposits in areas with positive loss & 1% to 66% with severe loss; I(No Exposure to Loss>Med) reflects lenders with 66% to 100% of deposits in areas with positive loss & 0% with severe loss. Charge-offs refers to the share of charged-off loans as a fraction of the four-quarter lagged loans. Note that the variable is in percentage points. Tier 1 Ratio refers to the bank equity capital as a fraction of assets. Note that the variable is in percentage points. Included but omitted from the table are the four-quarter lags of following controls: log of assets, deposits/assets, securities/assets, loans/assets, tier 1 capital ratio, real estate loans/loans, and roe. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. GDP II-III and Risk II-IV refers to the percentage of deposits located in counties designated to the corresponding GDP and weather Risk category. The fixed effects use the following abbreviations: b - bank, t - quarter, The standard-errors are clustered by bank and by quarter.

	Charge-offs		Tier1 Ratio		Log Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Q1 x High Exposure to Loss>Median	0.0111	0.0212**	0.0652**	0.0556	0.0050	0.0033
	(0.0091)	(0.0103)	(0.0324)	(0.0366)	(0.0044)	(0.0045)
Post Q2 x High Exposure to Loss>Median	0.0078	0.0195	-0.0125	-0.0236	0.0036	0.0013
	(0.0118)	(0.0136)	(0.0417)	(0.0423)	(0.0041)	(0.0046)
Post Q1 x Medium Exposure to Loss>Median	0.0053	0.0136	0.0329	0.0249	0.0156**	0.0142**
	(0.0082)	(0.0092)	(0.0496)	(0.0538)	(0.0068)	(0.0070)
Post Q2 x Medium Exposure to Loss>Median	-0.0055	0.0046	-0.0270	-0.0366	0.0157*	0.0136
	(0.0082)	(0.0089)	(0.0482)	(0.0539)	(0.0079)	(0.0087)
Post Q1 x No Exposure to Loss>Median		0.0201**		-0.0199		-0.0025
		(0.0089)		(0.0414)		(0.0041)
Post Q2 x No Exposure to Loss>Median		0.0285**		-0.0267		-0.0063
		(0.0112)		(0.0488)		(0.0052)
GDP II, (M)	-0.0091	-0.0138	-0.0629	-0.0584	-0.0230**	-0.0221**
	(0.0104)	(0.0104)	(0.0891)	(0.0898)	(0.0098)	(0.0098)
GDP III, (H)	-0.0261**	-0.0322**	-0.1932**	-0.1873*	-0.0342***	-0.0331***
	(0.0126)	(0.0129)	(0.0965)	(0.0975)	(0.0116)	(0.0118)
Risk, II Quartile	0.0274*	0.0210	0.4651***	0.4713***	-0.0265	-0.0253
	(0.0158)	(0.0157)	(0.1586)	(0.1596)	(0.0176)	(0.0176)
Risk, III Quartile	-0.0219	-0.0276*	0.0790	0.0845	0.0108	0.0118
	(0.0149)	(0.0153)	(0.1717)	(0.1706)	(0.0146)	(0.0146)
Risk, IV Quartile	0.0069	0.0015	0.0269	0.0321	-0.0218	-0.0208
	(0.0161)	(0.0160)	(0.1441)	(0.1433)	(0.0221)	(0.0222)
R^2	0.27856	0.27915	0.80034	0.80034	0.99415	0.99415
Observations	38,417	38,417	38,417	38,417	38,417	38,417
b fixed effects	✓	✓	✓	✓	✓	✓
t fixed effects	✓	✓	✓	✓	✓	✓

Table 8: Impact of Natural Hazards on Bank Performance and Lending: Local vs Non-local Lenders

The table is based on Table 7 and it divides each sample depending on whether the lender's deposits are concentrated in one county: 1 = local banks have more than 66% of deposits in one county. The table list estimates from: $Y_{bt} = \sum_{j=\{3,6\}} \beta_j^h \mathrm{I(t=j)} \times \mathrm{I(High\ Exposure\ to\ Loss{>}Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^m \mathrm{I(t=j)} \times \mathrm{I(Medium\ Exposure\ to\ Loss{>}Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^l \mathrm{I(t=j)} \times \mathrm{I(No\ Exposure\ to\ Loss{>}Med)}_{be} + \gamma Z_{bt} + \alpha_b + \gamma_t + \epsilon_{bt}$ where Y_{bt} stands for a performance or lending measure for bank b, during quarter closest to month t. I(High Exposure to Loss>Med) is an indicator for lenders with 66% to 100% of deposits in areas with positive loss & 66% to 100% with above-median (severe) loss; I(Medium Exposure to Loss>Med) stands for lenders with 66% to 100% of deposits in areas with positive loss & 1% to 66% with severe loss; I(No Exposure to Loss>Med) reflects lenders with 66% to 100% of deposits in areas with positive loss & 0% with severe loss. Charge-offs refers to the share of charged-off loans as a fraction of the four-quarter lagged loans. Note that the variable is in percentage points. Tier 1 Ratio refers to the bank equity capital as a fraction of assets. Note that the variable is in percentage points. Included but omitted from the table are the four-quarter lags of following controls: log of assets, deposits/assets, securities/assets, loans/assets, tier 1 capital ratio, real estate loans/loans, and roe. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. GDP II-III and Risk II-IV refers to the percentage of deposits located in counties designated to the corresponding GDP and weather Risk category. The fixed effects use the following abbreviations: b - bank, t - quarter, The standard-errors are clustered by bank and by quarter.

	Charge-offs		Tier1 Ratio		Log Loans	
Local Banks	0	1	0	1	0	1
	(1)	(2)	(3)	(4)	(5)	(6)
Post Q1 x High Exposure to Loss>Median	0.0177	0.0248**	0.0959*	0.0367	0.0045	0.0009
	(0.0121)	(0.0110)	(0.0516)	(0.0372)	(0.0056)	(0.0045)
Post Q2 x High Exposure to Loss>Median	0.0083	0.0288**	0.0297	-0.0293	0.0074	-0.0042
	(0.0129)	(0.0142)	(0.0742)	(0.0457)	(0.0061)	(0.0048)
Post Q1 x Medium Exposure to Loss>Median	0.0107	0.0161	0.0613	0.0204	0.0181**	0.0023
	(0.0087)	(0.0210)	(0.0594)	(0.0853)	(0.0085)	(0.0073)
Post Q2 x Medium Exposure to Loss>Median	0.0031	0.0089	-0.0093	-0.0058	0.0198*	-0.0004
	(0.0098)	(0.0137)	(0.0657)	(0.0772)	(0.0100)	(0.0080)
Post Q1 x No Exposure to Loss>Median	0.0267***	0.0166	0.0563	-0.0439	-0.0106	-0.0018
	(0.0100)	(0.0107)	(0.0892)	(0.0336)	(0.0094)	(0.0038)
Post Q2 x No Exposure to Loss>Median	0.0172*	0.0330**	0.0908	-0.0430	-0.0081	-0.0088
	(0.0103)	(0.0149)	(0.0988)	(0.0473)	(0.0110)	(0.0056)
GDP II, (M)	-0.0325*	-0.0099	-0.1763	-0.3173**	-0.0603***	0.0157
	(0.0189)	(0.0135)	(0.1511)	(0.1461)	(0.0219)	(0.0117)
GDP III, (H)	-0.0246	-0.0390*	-0.3410**	-0.4577**	-0.0466**	0.0107
	(0.0181)	(0.0227)	(0.1519)	(0.2028)	(0.0208)	(0.0183)
Risk, II Quartile	0.0141	0.1795	0.6950***	0.3124	-0.0263	-0.1699**
	(0.0206)	(0.1110)	(0.2277)	(0.6532)	(0.0268)	(0.0722)
Risk, III Quartile	-0.0152	-0.0251	0.3163**	2.680*	0.0300	-0.1086
	(0.0170)	(0.1173)	(0.1583)	(1.471)	(0.0210)	(0.0874)
Risk, IV Quartile	-0.0104	0.1078	0.1314	1.552**	-0.0075	-0.1996***
	(0.0185)	(0.0821)	(0.1676)	(0.7672)	(0.0319)	(0.0721)
R^2	0.30352	0.27375	0.78196	0.86108	0.99361	0.99154
Observations	22,078	16,348	22,078	16,348	22,078	16,348
b fixed effects	✓	✓	✓	✓	✓	✓
t fixed effects	✓	✓	✓	✓	✓	✓

Table 9: Impact of Natural Hazards on Bank Performance and Lending: Local vs Non-local Markets

The table is based on Table 7 and it divides each sample depending on whether the lender's deposits are located mostly in counties with above-median fraction of local finance: 1 = above 89% of deposits (equivalent to 75th percentile) in high-local-finance counties. The table list estimates from: $Y_{bt} = \sum_{j=\{3,6\}} \beta_j^h \text{I(t=j)} \times \text{I(High Exposure to Loss>Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^m \text{I(t=j)} \times \text{I(Medium Exposure to Loss>Med)}_{be} + \sum_{j=\{3,6\}} \beta_j^l \text{I(t=j)} \times \text{I(No Exposure to Loss>Med)}_{be} + \gamma Z_{bt} + \alpha_b + \gamma_t + \epsilon_{bt}$ where Y_{bt} stands for a performance or lending measure for bank b, during quarter closest to month t. I(High Exposure to Loss>Med) is an indicator for lenders with 66% to 100% of deposits in areas with positive loss & 66% to 100% with above-median (severe) loss; I(Medium Exposure to Loss>Med) stands for lenders with 66% to 100% of deposits in areas with positive loss & 1% to 66% with severe loss; I(No Exposure to Loss>Med) reflects lenders with 66% to 100% of deposits in areas with positive loss & 0% with severe loss. Charge-offs refers to the share of charged-off loans as a fraction of the four-quarter lagged loans. Note that the variable is in percentage points. Tier 1 Ratio refers to the bank equity capital as a fraction of assets. Note that the variable is in percentage points. Included but omitted from the table are the four-quarter lags of following controls: log of assets, deposits/assets, securities/assets, loans/assets, tier 1 capital ratio, real estate loans/loans, and roe. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. GDP II-III and Risk II-IV refers to the percentage of deposits located in counties designated to the corresponding GDP and weather Risk category. The fixed effects use the following abbreviations: b - bank, t - quarter, The standard-errors are clustered by bank and by quarter.

	Charge-offs		Tier1 Ratio		Log Loans	
Markets with High Local Finance	0	1	0	1	0	1
	(1)	(2)	(3)	(4)	(5)	(6)
Post Q1 x High Exposure to Loss>Median	0.0274**	0.0118	0.0525	0.0879**	0.0034	0.0005
	(0.0106)	(0.0117)	(0.0421)	(0.0388)	(0.0046)	(0.0044)
Post Q2 x High Exposure to Loss>Median	0.0198	0.0209*	-0.0067	0.0011	0.0034	-0.0020
	(0.0154)	(0.0120)	(0.0487)	(0.0463)	(0.0057)	(0.0063)
Post Q1 x Medium Exposure to Loss>Median	0.0175*	-0.0097	0.0488	-0.0664	0.0142*	0.0093
	(0.0098)	(0.0171)	(0.0589)	(0.1223)	(0.0076)	(0.0094)
Post Q2 x Medium Exposure to Loss>Median	0.0076	-0.0020	-0.0250	-0.0026	0.0144	0.0012
	(0.0093)	(0.0185)	(0.0616)	(0.1098)	(0.0088)	(0.0107)
Post Q1 x No Exposure to Loss>Median	0.0211**	0.0163	0.0023	-0.0484	0.0030	-0.0036
	(0.0098)	(0.0114)	(0.0409)	(0.0397)	(0.0040)	(0.0054)
Post Q2 x No Exposure to Loss>Median	0.0259**	0.0323*	-0.0670	0.0190	5.2×10^{-5}	-0.0082
	(0.0104)	(0.0172)	(0.0437)	(0.0614)	(0.0055)	(0.0078)
GDP II, (M)	-0.0168	0.0107	-0.0814	-0.5043**	-0.0322**	0.0204
	(0.0145)	(0.0175)	(0.1076)	(0.2167)	(0.0130)	(0.0133)
GDP III, (H)	-0.0234	-0.0386	-0.1850*	-0.4853*	-0.0321**	0.0081
	(0.0153)	(0.0328)	(0.0955)	(0.2896)	(0.0137)	(0.0212)
Risk, II Quartile	-0.0026	0.2598	0.4884***	-0.0730	0.0057	-0.0303
	(0.0183)	(0.2427)	(0.1815)	(0.6249)	(0.0226)	(0.0878)
Risk, III Quartile	-0.0306	0.3236	0.1187	0.6669	0.0133	-0.1239
	(0.0190)	(0.2377)	(0.1347)	(1.209)	(0.0166)	(0.1578)
Risk, IV Quartile	-0.0169	0.4248*	0.0296	-0.4829	-0.0204	-0.1924
	(0.0167)	(0.2402)	(0.1313)	(1.301)	(0.0243)	(0.1552)
R^2	0.30204	0.30134	0.82656	0.84972	0.99428	0.99279
Observations	28,770	9,656	28,770	9,656	28,770	9,656
b fixed effects	✓	✓	✓	✓	✓	✓
t fixed effects	✓	✓	✓	✓	✓	✓

Table 10: Impact of Natural Hazards on Bank Performance and Lending: Only Local Lenders

The table list estimates from: $Y_{bcte} = \sum_{j=\{3,6\}} \beta^h_j \mathrm{I(t=j)} \times \mathrm{I(Loss>Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce} + \sum_{j=\{3,6\}} \beta^l_j \mathrm{I(t=j)} \times \mathrm{I(Loss>Med)}_{ce} \times \mathrm{I(Non\text{-}Local\ Finance)}_{be} + \sum_{j=\{3,6\}} \sigma^h_j \mathrm{I(t=j)} \times \mathrm{I(Loss<Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{be} + \gamma Z_{bte} + \alpha_{bce} + \gamma_{ste} + \epsilon_{bcte}$ where Y_{bcte} is a performance or lending measure for bank b, in county c, at time t, during event e. The sample includes only local lenders, with more than 66% of deposits located in one county. $\mathrm{I(Loss>Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce}$ is an indicator for whether the lender is located in a county with above-median loss which also has above-median share of local deposits. $\mathrm{I(Loss>Med)}_{ce} \times \mathrm{I(Non\text{-}Local\ Finance)}_{ce}$ is an indicator for a lender in a high-impact county where the share of local deposits is below the median. $\mathrm{I(Loss<Med)}_{ce} \times \mathrm{I(Local\ Finance)}_{ce}$ is an indicator for a local lender residing in a county with below-median loss where local finance is more prevalent. Charge-offs refers to the share of charged-off loans as a fraction of the four-quarter lagged loans. Note that the variable is in percentage points. Tier 1 Ratio refers to the bank equity capital as a fraction of assets. Note that the variable is in percentage points. Included but omitted from the table are the four-quarter lags of following controls: log of assets, deposits/assets, securities/assets, loans/assets, tier 1 capital ratio, real estate loans/loans, and roe. Post Q1/Q2 correspond to the indicators for 3/6 months after the landfall. The fixed effects use the following abbreviations: c - county, i - industry, e - event, t - month, s - state, gdp - income group, risk - risk group. Risk group is based on the quartile of expected loss within the state. Income group is based on the tercile of county income. The standard-errors are two-way clustered by the two sets of fixed effects.

	Charge-offs		Tier1 Ratio		Log Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Loss>Median x Post Q1	0.0327**		0.0302		-0.0050*	
	(0.0130)		(0.0432)		(0.0026)	
Loss>Median x Post Q2	0.0202		0.0047		-0.0071**	
	(0.0199)		(0.0546)		(0.0032)	
Loss>Median x Post Q1 x Local Fin		0.0468***		0.0218		-0.0085***
		(0.0171)		(0.0561)		(0.0032)
Loss>Median x Post Q2 x Local Fin		0.0432*		-0.0215		-0.0135***
		(0.0254)		(0.0750)		(0.0044)
Loss>Median x Post Q1 x Non-Local Fin		0.0411**		0.1359		-0.0093*
		(0.0201)		(0.0840)		(0.0055)
Loss>Median x Post Q2 x Non-Local Fin		0.0160		0.1379		-0.0122**
		(0.0288)		(0.0961)		(0.0058)
Loss<Median x Post Q1 x Local Fin		0.0215		0.0572		-0.0065**
		(0.0141)		(0.0471)		(0.0031)
Loss<Median x Post Q2 x Local Fin		0.0214		0.0531		-0.0099**
		(0.0191)		(0.0634)		(0.0042)
R^2	0.62439	0.62452	0.97269	0.97271	0.99912	0.99912
Observations	15,228	15,228	15,228	15,228	15,228	15,228
c-b-e fixed effects	✓	✓	✓	✓	✓	✓
t-s-risk-gdp fixed effects	✓	✓	✓	✓	✓	✓

Table 11: Sensitivity of Local Finance Definition

The table is based on the results in Table 6. Each column uses a different specification for local deposits, based on whether more than 66% (baseline), 75%, 90%, or 99% of a bank's deposits are located in one county. The column (5) defines as local a bank with less than $1B in assets. For additional definitions, please consult Table 6.

	$\Delta \ln Emp$				
	66%	75%	90%	99%	Small
	(1)	(2)	(3)	(4)	(5)
Loss>Med x Post Q1 x High Local Fin	-0.0062**	-0.0051*	-0.0015	-0.0007	0.0021
	(0.0027)	(0.0028)	(0.0021)	(0.0020)	(0.0029)
Loss>Med x Post Q2 x High Local Fin	-0.0030	-0.0024	0.0003	-0.0030	0.0025
	(0.0027)	(0.0026)	(0.0022)	(0.0022)	(0.0029)
Loss>Med x Post Q1	-0.0005	-0.0007	-0.0025	-0.0030*	-0.0039***
	(0.0017)	(0.0018)	(0.0015)	(0.0015)	(0.0015)
Loss>Med x Post Q2	0.0005	0.0005	-0.0009	0.0009	-0.0014
	(0.0017)	(0.0019)	(0.0017)	(0.0017)	(0.0016)
Post Q1 x High Local Fin	0.0003	-0.0016	-0.0015	0.0005	0.0017
	(0.0017)	(0.0017)	(0.0015)	(0.0016)	(0.0018)
Post Q2 x High Local Fin	-0.0001	-0.0023	-0.0020	-0.0004	0.0031
	(0.0017)	(0.0017)	(0.0016)	(0.0018)	(0.0020)
R^2	0.79938	0.79940	0.79933	0.79934	0.79936
Observations	95,603	95,603	95,603	95,603	95,603
c-i-e fixed effects	✓	✓	✓	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓	✓	✓	✓

Table 12: Block-buster Events

The table is based on the results in Table 6. Each column is based on a sub-sample from a specific hurricane: Katrina, Sandy, Harvey, or Ike. For additional definitions, please consult Table 6.

	$\Delta \ln Emp$				
	All	Katrina	Sandy	Harvey	Ike
	(1)	(2)	(3)	(4)	(5)
Loss>Med x Post Q1 x High Local Fin	-0.0062**	-0.0097	-0.0196*	-0.0482*	0.0146
	(0.0027)	(0.0107)	(0.0103)	(0.0281)	(0.0180)
Loss>Med x Post Q2 x High Local Fin	-0.0030	-0.0288**	-0.0069	0.0004	0.0325
	(0.0027)	(0.0123)	(0.0100)	(0.0213)	(0.0218)
Loss>Med x Post Q1	-0.0005	-0.0074	-0.0073	0.0652	-0.0022
	(0.0017)	(0.0050)	(0.0070)	(0.0587)	(0.0138)
Loss>Med x Post Q2	0.0005	-0.0015	0.0043	0.0248	-0.0039
	(0.0017)	(0.0055)	(0.0085)	(0.0367)	(0.0081)
Post Q1 x High Local Fin	0.0003	0.0166*	0.0097*	0.0318	-0.0109
	(0.0017)	(0.0100)	(0.0058)	(0.0194)	(0.0118)
Post Q2 x High Local Fin	-0.0001	0.0061	0.0025	-0.0006	-0.0107
	(0.0017)	(0.0102)	(0.0081)	(0.0153)	(0.0129)
R^2	0.79938	0.67339	0.86019	0.56164	0.73284
Observations	95,603	4,384	2,841	1,257	1,325
c-i-e fixed effects	✓	✓	✓	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓	✓	✓	✓

Figure 1: Spatial Distribution: Impacted Areas, Risk, Local Finance, Income

From the first row down: Figure 1 represents the total number of disaster events in each county during 1998-2019. Category 7 refers to 7 or more events. Figure 2 represents the number of times a county has received above-median losses during the sample. Figure 3 represents the Risk category of each county in the sample. Each number corresponds to the quartile (relative to the state) of the expected loss during the sample. Figure 4 lists whether a county has above-state-median fraction of local deposits (1) or below (0). Figure 5 lists the state tercile of GDP for each county.

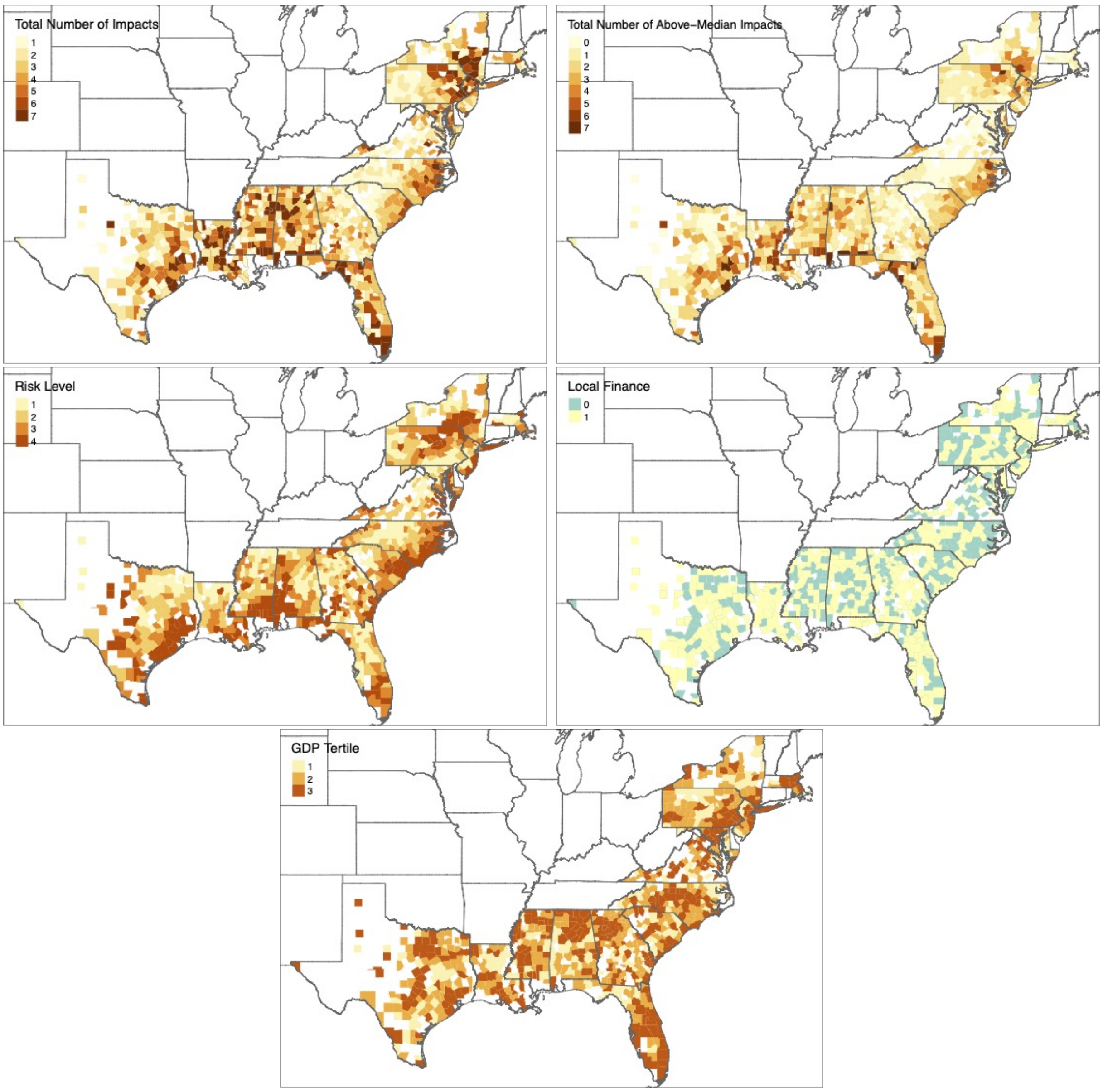


Figure 2: Employment Impact by Risk, Income, Industry

Figure 1 plots the coefficients from model 1 estimates separately for counties with below and above-median risk. Figure 2 plots uses the same specification estimated using the sample of counties in each of the three terciles of GDP. Figure 3 plots the industry-specific estimates of the coefficients in model 1 for the first post quarter.

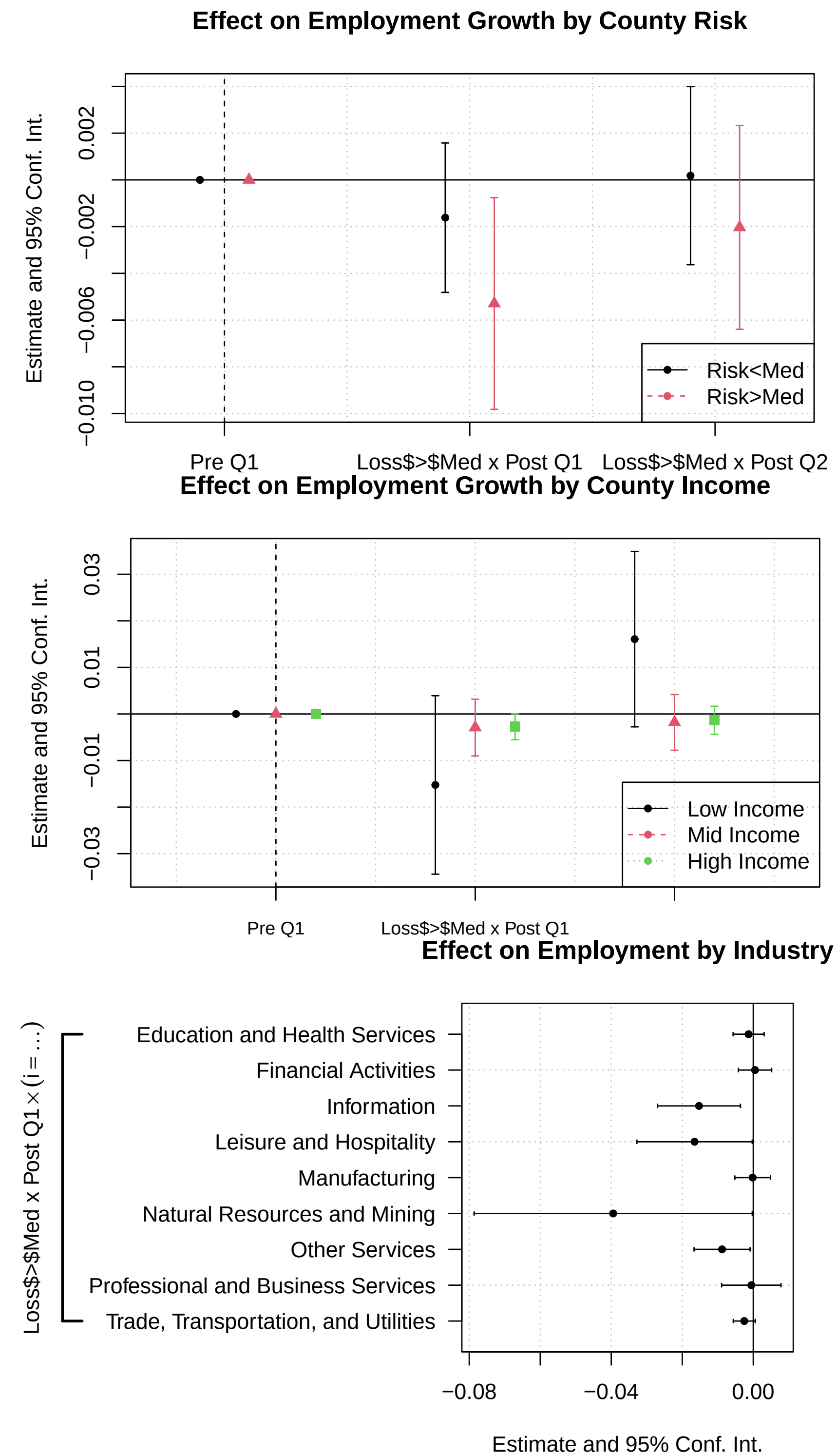
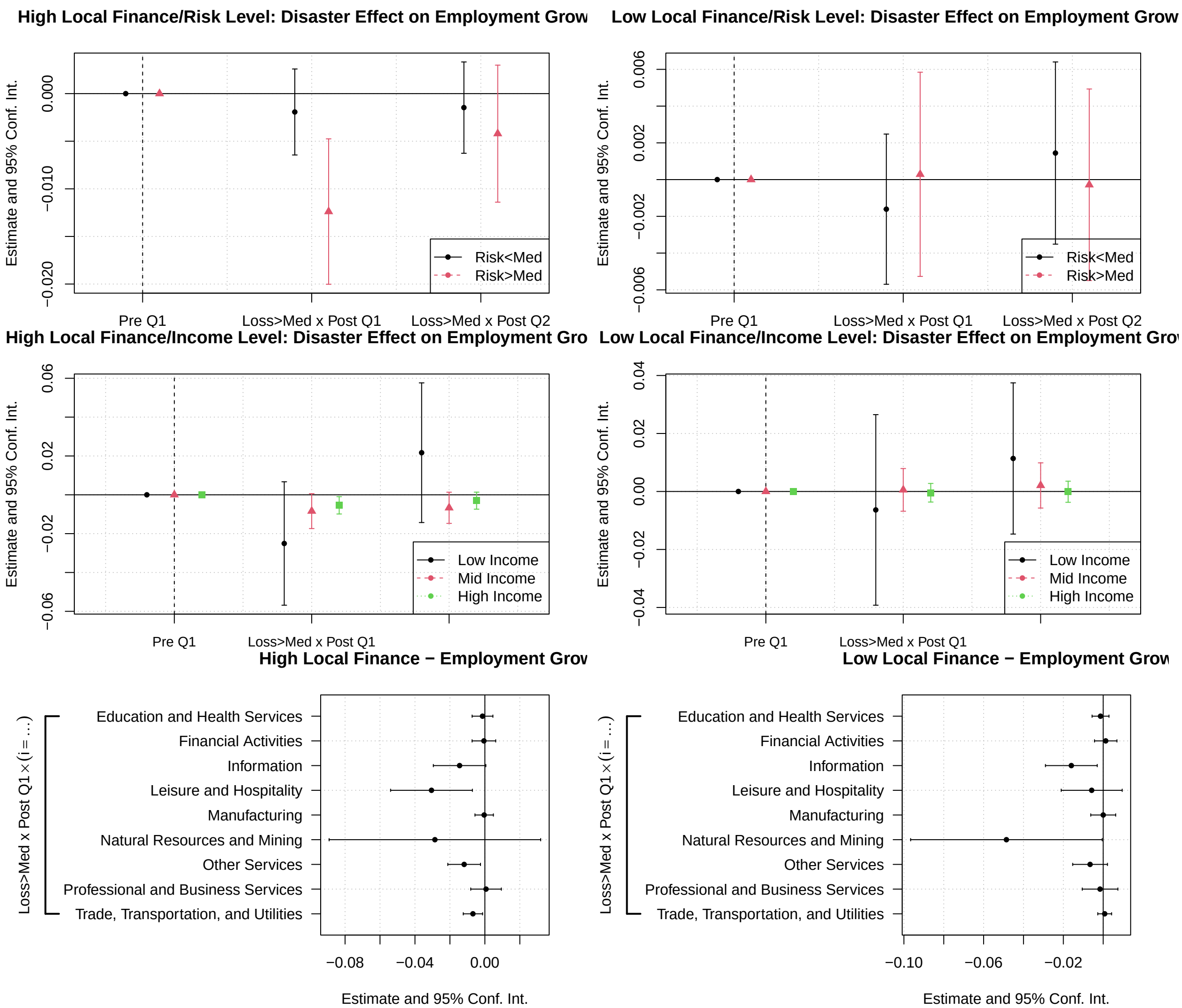


Figure 3: Local Finance: Employment Impact by Risk, Income, Industry

The first column lists estimates for the sample of counties with above-median share of local deposits, while the second column focuses on the sample of counties of below-median share. Figures in row 1 plots the coefficients from model 1 estimates separately for counties with below and above-median risk. Figures in row 2 plots uses the same specification estimated using the sample of counties in each of the three terciles of GDP. Figures in row 3 plots the industry-specific estimates of the coefficients in model 1 for the first post quarter.



Appendix (for online publication)

Appendix A: Robustness and Extensions

Table A1: Disaster Events at Counties by Type and State

The table lists the states included in the sample and distinguishes the types of natural hazards that occur in the sample.

State	**Flood/Storm**, N = 1,911	**Hurricane**, N = 1,638
AL	244 (72%)	97 (28%)
FL	110 (32%)	230 (68%)
GA	277 (59%)	193 (41%)
LA	145 (44%)	182 (56%)
MA	72 (92%)	6 (7.7%)
MD	20 (23%)	68 (77%)
MS	231 (67%)	116 (33%)
NC	51 (16%)	272 (84%)
NJ	57 (53%)	51 (47%)
NY	124 (70%)	53 (30%)
PA	162 (82%)	35 (18%)
SC	53 (46%)	63 (54%)
TX	287 (63%)	171 (37%)
VA	78 (44%)	101 (56%)

[1] n (%)

Table A2: Baseline Quarterly Employment Impact of Natural Hazards by Risk

The table extends the results in Table 4 by dividing counties into high- and low-risk samples. High-risk counties include the third and fourth quartile of the weather risk, while low-risk counties include the first two quartiles. For the additional information, please refer to the notes in Table 4.

	$\Delta \ln Emp$	
	Low Risk	High Risk
	(1)	(2)
Loss>Med x Post Q1	-0.0016	-0.0053**
	(0.0016)	(0.0023)
Loss>Med x Post Q2	0.0002	-0.0020
	(0.0019)	(0.0022)
R^2	0.78418	0.81944
Observations	43,968	52,364
c-i-e fixed effects	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓

Table A3: Summary Statistics by County Risk

The table is a variation of Table 1 where counties are divided by risk levels rather than by the level of impact. For additional information, please refer to the notes in Table 1.

		Risk Level	
Variable	**Overall**, N = 96,332	**I, Low**, N = 43,968	**II, High**, N = 52,364
Employment Growth (%)	0.4 (13.7) [-2.8, 2.8]	0.5 (12.5) [-2.5, 2.7]	0.3 (14.7) [-3.1, 2.9]
Employment Gr: Pre Q1	0.7 (12.7) [-2.3, 3.0]	0.6 (10.3) [-2.1, 2.8]	0.8 (14.3) [-2.5, 3.2]
Employment Gr: Post Q1-Q2	0.2 (14.2) [-3.1, 2.7]	0.4 (13.4) [-2.7, 2.6]	0.1 (14.9) [-3.4, 2.8]
Employment Gr:High Impact Pre Q1	0.8 (14.1) [-2.4, 3.1]	0.4 (9.3) [-2.4, 2.7]	1.1 (16.2) [-2.4, 3.4]
Employment Gr:High Impact Post Q1-Q2	0.1 (13.0) [-3.2, 2.8]	0.2 (10.5) [-2.8, 2.6]	0.0 (14.2) [-3.4, 2.8]
Damage (% GDP)	0.5 (1.4) [0.0, 0.3]	0.1 (0.4) [0.0, 0.1]	0.7 (1.8) [0.0, 0.5]
Impact			
I, Low	49,383 (51%)	26,778 (61%)	22,605 (43%)
II, High	46,949 (49%)	17,190 (39%)	29,759 (57%)
Personal Income ($B)	9 (19) [1, 7]	9 (16) [1, 10]	8 (21) [1, 5]
Population (10k)	21 (40) [3, 20]	23 (33) [4, 28]	19 (45) [3, 15]
Share of local Deposits (%)	24 (25) [1, 40]	23 (24) [3, 38]	25 (25) [0, 42]
Local Finance			
I, Low	50,605 (53%)	23,657 (54%)	26,948 (51%)
II, High	45,727 (47%)	20,311 (46%)	25,416 (49%)
GDP Tertile			
GDP I (L)	22,565 (23%)	6,681 (15%)	15,884 (30%)
GDP II (M)	34,088 (35%)	15,520 (35%)	18,568 (35%)
GDP III (H)	39,679 (41%)	21,767 (50%)	17,912 (34%)

[1] Mean (SD) [IQR]; n (%)

Table A4: Monthly Event Study: Employment Impact of Natural Hazards by Risk

The table is a variation of Table 4. Here, I report the monthly coefficients of the event study in Table 4 as opposed to quarterly coefficients. The sample in this estimation includes monthly observations for employment growth and the event includes four months before and seven months after the landfall. Month zero, which precedes the disaster is omitted. Column (1) reports estimates from the full sample, while (2) and (3) are based on samples of counties with above/below median risk of severe weather. For additional information, please refer to the notes of Table 4.

	$\Delta \ln Emp$		
	Full Sample	Low Risk	High Risk
	(1)	(2)	(3)
Loss>Med x j=-3	0.0007	9.55×10^{-5}	0.0017*
	(0.0006)	(0.0007)	(0.0010)
Loss>Med x j=-2	0.0003	0.0002	0.0007
	(0.0006)	(0.0008)	(0.0009)
Loss>Med x j=-1	-0.0009*	-0.0013*	-0.0002
	(0.0005)	(0.0008)	(0.0008)
Loss>Med x j=+1	-0.0021***	-0.0011	-0.0032***
	(0.0006)	(0.0008)	(0.0009)
Loss>Med x j=+2	-0.0012**	-0.0013	-0.0011
	(0.0006)	(0.0008)	(0.0009)
Loss>Med x j=+3	-0.0005	0.0007	-0.0019**
	(0.0005)	(0.0007)	(0.0009)
Loss>Med x j=+4	-0.0007	0.0001	-0.0019*
	(0.0006)	(0.0008)	(0.0010)
Loss>Med x j=+6	-0.0013*	-0.0007	-0.0020**
	(0.0007)	(0.0010)	(0.0010)
Loss>Med x j=+5	-0.0005	0.0003	-0.0014
	(0.0008)	(0.0014)	(0.0011)
Loss>Med x j=+7	-3.5×10^{-5}	-0.0005	0.0004
	(0.0005)	(0.0007)	(0.0008)
R^2	0.71018	0.69197	0.72750
Observations	326,349	150,643	175,706
c-i-e fixed effects	✓	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓	✓

Table A5: Local Finance and Quarterly Employment Impact of Natural Hazards by Risk

The table extends Table 6 by dividing the sample by counties with below/above-median risk of severe weather. For additional information, please refer to the notes in Table 6.

	$\Delta \ln Emp$	
	Low Risk	High Risk
	(1)	(2)
Loss>Med x Post Q1 x High Local Fin	-0.0019	-0.0124***
	(0.0023)	(0.0039)
Loss>Med x Post Q2 x High Local Fin	-0.0015	-0.0042
	(0.0024)	(0.0037)
Loss>Med x Post Q1 x Low Local Fin	-0.0016	0.0003
	(0.0021)	(0.0028)
Loss>Med x Post Q2 x Low Local Fin	0.0014	-0.0003
	(0.0025)	(0.0027)
Post Q1 x High Local Fin	-0.0007	0.0021
	(0.0019)	(0.0034)
Post Q2 x High Local Fin	-0.0014	0.0021
	(0.0020)	(0.0034)
R^2	0.78360	0.81540
Observations	43,577	52,026
c-i-e fixed effects	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓

Table A6: Summary Statistics by Local Finance only for High-Risk Counties

The table replicates Table 5 by restricting the sample to only counties with high risk of severe weather. For additional information, please refer to the notes in Table 5.

		Local Finance	
Variable	**Overall**, N = 17,912	**I, Low**, N = 10,332	**II, High**, N = 7,580
Risk Level			
II, High	17,912 (100%)	10,332 (100%)	7,580 (100%)
Employment Growth (%)	0.2 (9.6) [-2.3, 2.4]	0.3 (10.1) [-2.1, 2.5]	0.0 (8.9) [-2.6, 2.3]
Employment Gr: Pre Q1	0.1 (8.9) [-2.0, 2.4]	0.4 (9.4) [-1.7, 2.4]	-0.2 (8.1) [-2.3, 2.4]
Employment Gr: Post Q1-Q2	0.2 (9.9) [-2.5, 2.4]	0.3 (10.4) [-2.3, 2.5]	0.1 (9.3) [-2.7, 2.3]
Employment Gr:High Impact Pre Q1	0.4 (9.3) [-1.9, 2.3]	0.6 (10.1) [-1.7, 2.3]	0.1 (8.1) [-2.0, 2.4]
Employment Gr:High Impact Post Q1-Q2	0.3 (9.9) [-2.4, 2.4]	0.3 (10.7) [-2.3, 2.4]	0.2 (8.6) [-2.7, 2.3]
Damage (% GDP)	0.7 (2.0) [0.0, 0.4]	0.8 (2.2) [0.0, 0.5]	0.6 (1.6) [0.0, 0.4]
Impact			
I, Low	8,641 (48%)	4,918 (48%)	3,723 (49%)
II, High	9,271 (52%)	5,414 (52%)	3,857 (51%)
Personal Income ($B)	18 (34) [3, 15]	18 (30) [3, 15]	19 (39) [2, 14]
Population (10k)	43 (71) [8, 40]	45 (69) [10, 41]	40 (72) [7, 31]
Share of local Deposits (%)	18 (19) [3, 27]	10 (11) [0, 16]	30 (21) [13, 45]
GDP Tertile			
GDP III (H)	17,912 (100%)	10,332 (100%)	7,580 (100%)

[1] n (%); Mean (SD) [IQR]

Table A7: Monthly Event Study: Local Finance and Quarterly Employment Impact of Natural Hazards

The table is a variation of Table 6. Here, I report the coefficients from the monthly event study as opposed to quarterly coefficients. The sample in this estimation includes monthly observations for employment growth and the event includes four months before and seven months after the landfall. Month zero, which precedes the disaster is omitted. Column (1) reports estimates from the full sample, while (2) and (3) are based on samples of counties with above/below median risk of severe weather. Monthly coefficients ending in H refer to outcomes in counties with high local finance (above-median share of local deposits), while those ending in L refer to counties with low-local finance. For additional information, please refer to the notes in Table 6.

		$\Delta \ln Emp$	
	Full Sample	Low Risk	High Risk
	(1)	(2)	(3)
Loss>Med x j=-3.H	0.0016**	-0.0002	0.0038***
	(0.0008)	(0.0009)	(0.0014)
Loss>Med x j=-2.H	0.0012	0.0008	0.0019
	(0.0009)	(0.0010)	(0.0015)
Loss>Med x j=-1.H	-0.0004	-0.0019**	0.0015
	(0.0007)	(0.0010)	(0.0012)
Loss>Med x j=+1.H	-0.0032***	-0.0011	-0.0054***
	(0.0008)	(0.0009)	(0.0013)
Loss>Med x j=+2.H	-0.0022**	-0.0023**	-0.0023
	(0.0009)	(0.0011)	(0.0016)
Loss>Med x j=+3.H	-0.0011	0.0006	-0.0031**
	(0.0008)	(0.0008)	(0.0014)
Loss>Med x j=+4.H	-0.0015*	-0.0001	-0.0032**
	(0.0009)	(0.0011)	(0.0015)
Loss>Med x j=+5.H	-0.0011	-0.0014	-0.0009
	(0.0010)	(0.0013)	(0.0014)
Loss>Med x j=+6.H	-0.0008	-0.0006	-0.0013
	(0.0010)	(0.0012)	(0.0016)
Loss>Med x j=+7.H	0.0002	-0.0006	0.0010
	(0.0008)	(0.0009)	(0.0013)
Loss>Med x j=-3.L	-1.39×10^{-5}	0.0003	3.25×10^{-5}
	(0.0007)	(0.0009)	(0.0011)
Loss>Med x j=-2.L	-0.0004	-0.0004	-0.0002
	(0.0007)	(0.0009)	(0.0010)
Loss>Med x j=-1.L	-0.0013**	-0.0007	-0.0016*
	(0.0007)	(0.0009)	(0.0009)
Loss>Med x j=+1.L	-0.0013*	-0.0010	-0.0019*
	(0.0007)	(0.0009)	(0.0010)
Loss>Med x j=+2.L	-0.0003	-0.0003	-0.0004
	(0.0007)	(0.0011)	(0.0011)
Loss>Med x j=+3.L	-3.88×10^{-5}	0.0007	-0.0011
	(0.0007)	(0.0008)	(0.0011)
Loss>Med x j=+4.L	-3.6×10^{-5}	0.0003	-0.0008
	(0.0007)	(0.0010)	(0.0011)
Loss>Med x j=+5.L	-0.0014	-1.25×10^{-5}	-0.0027**
	(0.0008)	(0.0012)	(0.0012)
Loss>Med x j=+6.L	-0.0003	0.0012	-0.0015
	(0.0010)	(0.0019)	(0.0011)
Loss>Med x j=+7.L	-0.0002	-0.0004	-1.58×10^{-5}
	(0.0006)	(0.0009)	(0.0009)
R^2	0.71026	0.69202	0.72775
Observations	326,349	150,643	175,706
c-i-e fixed effects	✓	✓	✓
t-i-s-risk-gdp fixed effects	✓	✓	✓

Figure A1: Monthly Employment Impact: Overall and by Risk

This figure plot coefficients from Table A4. For additional information, please refer to the notes in Table A4.

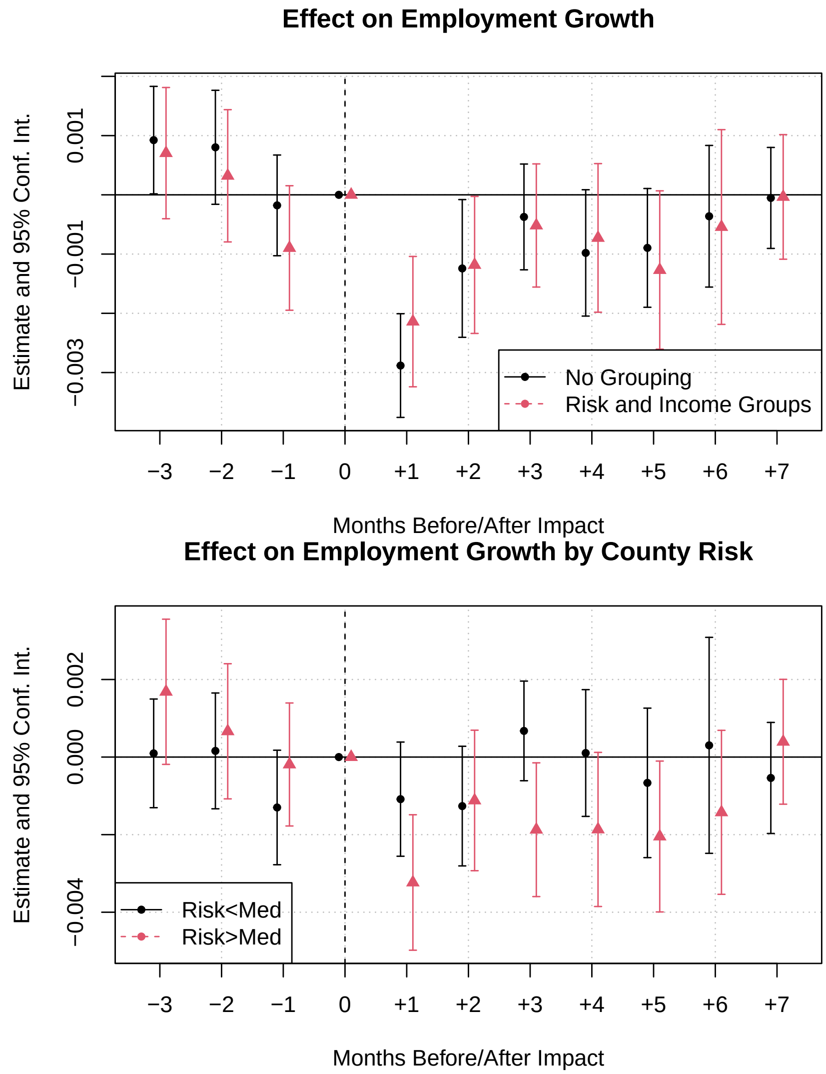


Figure A2: Monthly Employment Impact: Overall and by Risk

This figure plot coefficients from Table A7. For additional information, please refer to the notes in Table A7.