# The Economic Impact of Hurricanes in the US: Does Local Finance Matter?

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**Abstract**

Are un-diversified lenders a drag on the recovery from natural hazards, due to their exposure to systemic losses, or do they improve resilience, through their superior information? This study provides answers with a novel dataset of firm losses after hurricanes in US counties during 1999-2019, by comparing industry-specific employment across markets with different prevalence of concentrated lenders. I find that local finance mitigates job contractions for the average industry, particularly for vulnerable sectors, and for smaller firms. I document a novel mechanism that explains this observed correlation between economic resilience and local finance. I find that the role of local finance is sensitive to the credit supply conditions and improves resilience mostly when systemic portfolio losses are lower. I conclude that un-diversified local lenders improve resilience only when they retain sufficient capacity for additional lending.

JEL Classification:

Keywords: Natural Disasters, Bank Lending, Resilience, Community Banks, Employment shocks

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# 1 Introduction

Natural hazards reduce economic activity because businesses are vulnerable to severe weather.[1] Evidence suggests that access to credit limits the resulting volatility and speeds up recovery.[2] Some lenders may be in a better position to provide credit. For example, geographically diversified lenders can be critical for economic resilience, since credit supply from geographically concentrated banks can fall after systemic portfolio losses. However, diversified banks can turn to other markets and also reduce credit if damage to borrowers and their collateral reduces the profitability of new loans.[3] At the same time, reliance on soft information by local lenders enables lending even when risk increases (Berg and Schrader, 2012) and limits the effect of portfolio losses due to more prudent lending practices (Bolton et al., 2016).

Are un-diversified lenders a drag on the recovery from natural hazards or do they improve resilience? Is this due to mounting portfolio losses or increased risk of lending after landfall? This study attempts to answer these with a novel dataset of firm losses after hurricanes in US counties during 1999-2019. I compare sectoral employment across counties with varying commercial losses and test whether the prevalence of smaller lenders dampens or amplifies job contractions for specific vulnerable industries. I measure dependence on un-diversified lenders using the proportion of deposits supplied by banks whose deposits are mostly concentrated in one county. I estimate a quasi difference-in-difference model of industry-specific jobs growth in counties with firm loss during the three months before/after landfall and identify the effects of losses and local finance using continuous measures.[4] To shed light on the mechanisms behind the role of the local bank industry, I examine the sensitivity of the effect of local finance to changes in borrower risk and in the quality of the portfolio of existing loans. This provides important details about the economic impact of natural hazards – do they tend to exacerbate information frictions or mostly cause defaults on existing loans.

[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] The model does not cast counties into treated or control groups but, instead, identifies the marginal impact of business loss on industry jobs growth and its interaction with local finance.

The role of concentrated lenders is at the heart of the bank diversification literature, which studies how the spread of lender's portfolio across several markets impacts returns and economic volatility. Morgan et al. (2004) suggest that single-market lenders amplify shocks that reduce bank's funding – due to systemic portfolio losses or deposit withdrawals (supply shocks), and minimize shocks that reduce creditworthiness of new borrowers – due to destruction of collateral or reduced borrower income (demand shocks). However, there is evidence of a trade-off between the scale economies from a diversified portfolio and diseconomies due to the limited capacity to process soft information.[5] This can soften the sensitivity of local lenders to supply shocks and make their impact empirically ambiguous.

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. For example, 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 the financial sector development improves recoveries but there is also evidence that disasters, themselves, can directly impact lenders.[6]

I build on Cortés (2014) by studying the industry-specific jobs impact of hurricanes at counties with firm losses. This allows me to specifically focus on vulnerable industries and saturate my empirical model with invariant county by industry fixed effects and time-varying state by industry effects. Existing studies of the role of lenders do not distinguish business losses or employment at vulnerable industries. In contrast, I rely on a novel measure of commercial losses, which is key for identifying how local finance mitigates the financial challenges of vulnerable businesses, which are distinct from those of residents.

I provide novel evidence about why local lenders play a key role. Because small and

[5]This tradeoff is discussed by Acharya et al. (2006) and Tabak et al. (2011).

[6]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).

young firms benefit more, Cortés (2014) argues that local lenders alleviate acute asymmetric information after natural hazards. However, there is evidence that information advantage can also improve the recovery because it limits local lenders' sensitivity to supply shocks. Bolton et al. (2016) show that lenders reliant on proprietary soft information retain a capital buffer by charging higher spreads before a crisis. This allows them to continue to lend even during crisis periods and limits defaults.[7] Schüwer et al. (2019) provide evidence that these lenders improve the recovery. I test for the effect of each in two ways. First, I exploit differences in pre-hurricane concentration of county activity and industry-specific variation in productivity across counties. I use a triple-difference specification to estimate whether the recovery effect of local finance depends on pre-existing local differences that can affect information frictions or portfolio losses after the landfall. I hypothesize that higher concentration of activity in one industry or census tract within the county increases the correlation of defaults after a hurricane and raises systemic portfolio risk for local lenders. I test if the recovery impact of local finance varies when local loss is similar but pre-existing concentration of activity increases the correlation of defaults. I also test if the recovery effect of local finance is weaker in counties where an industry has higher productivity and is likely subject to less acute asymmetric information after landfall. Second, I use bank data to focus on lenders with similar information advantage but different systemic risk exposure due to their size.[8]

I find that local finance mitigates job contractions for the average industry, particularly for vulnerable sectors, and for small firms. Local finance reduces employment volatility both when damages are substantial and when hurricanes are less destructive. Funding disruptions appear less severe in counties where local banks play a bigger role, resulting in limited contractions and faster recovery. Counties with more diversified banks have lower resilience.

The resilience effect of local finance appears more sensitive to supply rather than demand shocks. Local lenders improve the recovery for firms with higher productivity, which are less

[7]Schwert (2018) also shows that lenders to bank-dependent firms tend to be well-capitalized.

[8]This follows evidence from Wheelock and Wilson (2001), which shows that as lenders increase in size, they achieve sufficient diversification of idiosyncratic risk and are more sensitive to systemic market conditions.

likely to be subject to higher information frictions. This stronger impact of un-diversified lenders in areas where information asymmetry is expected to be less acute suggests that their information advantage may be less critical. On the other hand, local lenders limit job contractions much less when they face higher systemic portfolio risk, in counties with higher industrial or geographic concentration. Bank evidence confirms that lenders with higher exposure to systemic risk, see loan portfolio deteriorations and provide less business loans. The results indicate that the positive effect of local finance is driven by concentrated lenders with low exposure to systemic risk which continue to lend after hurricanes.

My key contributions are threefold. First, I document a sector-specific employment impact of commercial losses from hurricanes for all events during 1999-2019. This extends the existing evidence, which mostly focuses on specific storms and does not distinguish commercial from residential damages.[9] Second, I show that local finance improves economic resilience and document a novel mechanism behind it. In contrast with previous evidence emphasizing the role of information frictions, I argue that un-diversified lenders improve resilience only when they are fairly small and avoid systemic portfolio losses. Third, I document that local lenders can vary in their exposure to natural hazards. I find that the loan portfolio of smaller banks is less exposed to the deterioration in local conditions and are able to expand lending after the landfall, which improves the resilience of the local economy.

The rest of the paper proceeds as follows: section 2 discusses related literature, section 3 details the data, section 4 considers the impact of local finance, while section 5 explores mechanism behind it. Section 6 includes robustness evidence and section 7 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

[9] For example, Basker and Miranda (2018) and Meltzer et al. (2021) show that the retail sector is vulnerable but only focus on two extreme hurricanes.

are transitory (Xiao and Nilawar, 2013) and sector-specific (Guimaraes et al., 1993). Local economies, as a whole, are resilient to natural hazards (Xiao and Feser, 2014).[10] Smaller firms, in industries requiring a store front take the brunt (Basker and Miranda, 2018; Meltzer et al., 2021). 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 show that smaller lenders with lower systemic risk exposure have lower portfolio losses and can improve local resilience by relying on proprietary soft information.

My evidence is also related to the literatures on bank diversification and relationship lending, particularly during periods of economic shocks. There is limited consensus on the benefits to banks of geographic diversification – risk can be diversified by reducing cross-market correlation of returns (Goetz et al., 2016) but risk can increase endogenously as lenders focus on risky loans and rely on higher leverage (Demsetz and Strahan, 1997). There is also evidence that very small local lenders are not sensitive to local economic conditions

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

(Yeager, 2004). As a results, both bigger multi-market lenders and smaller concentrated lenders can avoid a significant portfolio impact from natural hazards. Contrary to Morgan et al. (2004), this suggests that the local economies subject to supply shocks may not experience higher economic volatility with more single-market lenders. In addition, new evidence from the literature on relationship lending during economic shocks implies that lenders that utilize proprietary soft information and provide relationship loans, support lending after shocks (Bolton et al., 2016). My results support Bolton et al. (2016) by showing that small – likely relationship-based, banks support the recovery with new lending, as long as they manage to avoid direct portfolio losses.

# 3 Data and Sample Selection

This section includes details about the two datasets I use to characterize the economic and financial impact of hurricanes that made landfall in the US during 1999-2019.[11] The first focuses on industry-specific county jobs growth and the second is based on bank-specific lending and portfolio quality for community banks. I discuss the measure of commercial losses and the industries considered to be vulnerable. After that, I describe how I determine the markets where local lenders play an important role. Finally, I discuss the sample of bank observations, which focuses on lenders concentrated in a handful of markets with positive commercial losses.

**Commercial and Residential Loss form Hurricanes**

Information about hurricanes and exact date of landfall in each county comes from the list of presidential disaster declarations.[12] I measure commercial and residential loss from each event based on data from the following government programs: Individuals and Households Program (IHP); Small Business Administration's Disaster Loans (SBA); Public Assistance (PA); National Flood Insurance Program (NFIP). Each source provides county-level esti-

[11] The total includes unique combinations of events which affected the same county within a short period.

[12] Disaster declaration data is available on FEMA's website. These usually include a start and end date for each disaster. I use the end date to define the month of impact for each.

mates for every disaster declaration.[13] Business loss includes building and contents damage from business SBA loans, public property loss from the PA, and commercial flood-insurance claims from NFIP. Public damage is classified as commercial loss in order to quantify business interruptions caused by the loss of utilities and public infrastructure. Residential loss includes damage from IHP, building and content damage for residential SBA loans, and homeowner flood-insurance claims from NFIP. Losses are scaled by last year's county GDP to reflect the intensity of the impact between counties with different levels of development.

When studying the role of local finance in the recovery, I focus on counties with commercial losses. This generally includes places with residential loss, because the correlation between the two is 0.72.[14] Table 1 shows that damage at the average county is closely matched between commercial and residential: $28M and $25M, respectively, or 0.85% and 0.63% in terms of GDP fractions. Public loss makes up 60% of total business damage, while SBA and NFIP loss contribute 34% and 6%. This is consistent with the empirical literature suggesting that indirect loss due to destruction of infrastructure and utilities plays a major role in firm closures and financial loss (Webb et al., 2000).

The sample of events includes hurricanes that vary in geographic scope, intensity, and the extent of impact on businesses. Table 2 provides a complete list of all events, along with the number of affected counties and relative damage. Severe hurricanes tend to cause significant and uniform loss at the mean and tail of the distribution. However, the majority of events generate sizable loss within a handful of counties, and affect only the tail of the distribution. Hurricanes tend to be more frequent and generate higher losses in southern states, as seen in Table A1, but can be just as destructive albeit infrequent in the northeast.

I exclude Orleans Parish, St. Bernard Parish, and Hancock County, which where severely affected by Hurricane Katrina, with relative damage approaching 100%. They experienced significant long-term effects which I cannot properly capture within my short-term analysis.

[13]NFIP provides date of insurance claims. I associate claims to a particular hurricane if they fall within the disaster declaration period in the county.

[14]During historic events such as Katrina, Sandy, and Harvey this correlation is even higher: 0.83, 0.81, and 0.73, respectively.

**Vulnerable Industries and Employment Data**

I use monthly industry-specific county job growth, based on a variation on the two-digit NAICS classification. I focus on the dynamics of recovery for a subset of industries which are likely to suffer losses after a landfall, following evidence that not all sectors are impacted.[15]

I exclude Natural Resources and Mining, Construction, Information, Finance Insurance and Real Estate (FIRE), Education, and Health. I drop Natural Resources and Mining because my measure of losses does not directly capture agricultural or mining damage. Construction is excluded based on evidence from Guimaraes et al. (1993) that it benefits from higher demand for necessary repairs after hurricanes. Higher revenue makes it unlikely that this sector relies on local lenders in order to recover from direct losses.

To make a decision on whether to include the rest of the sectors, I use a limited dataset on individual SBA loans from a subset of 13 hurricanes. This dataset was acquired through a Freedom of Information Request and includes the industry classification for businesses that borrowed after hurricanes. Table A2 in the appendix lists the industrial composition of borrowers. We can see that Information, Education and Health make up a small portion of affected businesses according to this data. Decomposing FIRE by 4-digit NAICS codes shows that most of businesses rent real estate, which reflects residential loss.

The final set of industries in the sample is as follows: Manufacturing; Trade, Transportation, and Utilities; Professional and Business Services; Leisure and Hospitality; Other Services. Table 1 shows that they account for 55% of private employment, with Trade, Transportation, and Utilities, Manufacturing, and Leisure and Hospitality making up 25%, 16%, and 12%, respectively. These proportions are similar for counties with and without commercial losses, suggesting that hurricane risk does not vary with industrial composition. The monthly employment growth for the average industry in a county is 0.13%. Employment growth at smaller (less than 20 workers) or younger firms (less than 3 years) is higher, at 0.28% and 0.48%, respectively. Data for employment growth during 1999-2019 comes from

[15] For example, see Guimaraes et al. (1993); Webb et al. (2000); Ewing et al. (2003).

the Bureau of Labor Statistics (BLS). Some estimations use quarterly establishment and earnings data from the BLS, and quarterly employment by establishment size and age from the Quarterly Workforce Indicators (QWI).[16]

**Measure of Local Finance**

My proxy for the importance of to local finance uses the definition of community banks from Meyer and Yeager (2001) and Cortés (2014). Local lenders are banks with over 65% of deposits located in one county. The county where these deposits are located is considered to be the home of this bank. I measure the role of local finance in a county with the fraction of total home-bank deposits. Alternatively, I use the log of home deposits, the fraction of local banks, and the log of local banks. Information about the geographic distribution of deposits comes from the Summary of Deposits. Table 1 shows that the average county has about 2 local and 7 non-local banks. Local deposits make up 26% of the total, which closely follows the bank distribution. This variable is the key measure of access to local credit in this study.

**Bank Data**

I study the impact of hurricanes on the financial condition of local lenders by focusing on banks with a home in a county with commercial loss. Quarterly balance sheet data comes from Call Reports. The dataset for this analysis includes observations for the two quarters before a hurricane and the quarter after. Summary statistics for this are available in Table 3. Since the sample of banks includes only home lenders, they are fairly small, with average assets of $333M.

**Firm Concentration and Productivity**

I also rely on variation in the way hurricanes impact the financial condition of lenders depending on pre-existing difference in the industrial concentration and productivity. I measure county industrial concentration based on the HHI index using sectoral GDP data from the Bureau of Economic Analysis (BEA) for 2000-2018. The geographic concentration measure uses census tract employment from Census's Longitudinal Employer-Household Dynamics

[16] For the majority of states the QWI data starts in 2000 and ends in 2018.

Data. The measure of productivity is industry-specific and is based on earnings.

# 4 Local Lenders and Employment Recovery

According to Zhang et al. (2009), there are distinct reasons why hurricanes impact firms. They reduce capital since fixed assets have low mobility and are vulnerable to severe weather. They disrupt labor supply directly – due to injuries or out-migration, or indirectly – due to higher demand from other industries. Upstream disruptions or infrastructure damage limit lifelines and cause indirect losses. Prolonged closures reduce customers by redirecting demand elsewhere. In this section, I focus on the difference in the short-run recovery in jobs growth across markets with different prevalence of local lenders, in order to examine whether the local banking structure is likely to limit the consequences of business vulnerability.

## Expected Effect of Access to Local Lenders

Firms will likely face additional costs after a landfall in order to replace capital, retain employees, access suppliers, and limit down-time.[17] This is a financial challenge when revenue is disrupted and often forces firms to rely on credit or savings in order to restore operations. Consistent with this, Collier et al. (2020) finds that about 40% of firms affected by hurricane Sandy took on additional debt. Del Ninno et al. (2003) and Cortés and Strahan (2017) provide additional evidence that credit demand increases after natural hazards.

Access to credit is key for a quick recovery, as argued by Noy (2009) and Keerthiratne and Tol (2017), however, severe weather can disrupt the provision of local credit for two separate reasons. On the demand side, damage to firm capital reduces collateral available to secure credit and makes borrowers more risky. Consistent with this Berg and Schrader (2012) show that there was a significant reduction in the probability of loan approval after volcanic activity. On the supply side, increased defaults on existing loans can impair bank

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

equity and limit lender's ability to supply credit (Schwert, 2018).[18]

The sensitivity to demand and supply factors can vary across lenders, suggesting that the local bank structure may be key for the economic recovery. For example, lenders which base credit decisions on proprietary soft information can be less impacted by demand shocks. Bolton et al. (2016) argues that relationship banks located close to firms gather information at an ongoing basis and provide stable credit over time. Collecting information about close-by firms is cheaper, allowing banks to not only charge higher prices (Agarwal and Hauswald, 2010) but also extend more credit when necessary. Lenders can develop market-specific information advantage related to all firms in a specific market, which can also make them less sensitive to demand shocks (Paravisini et al., 2015). 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. Since smaller lenders have an organizational advantage in relationship lending (Berger et al., 2005) and are likely to specialize in lending to a specific market, the evidence implies that markets where smaller lenders play a dominant role are less impacted by the reduction in collateral values and the increase in uncertainty after landfall.

Credit disruptions will also vary across markets depending on the severity of the impact on the quality of the existing loan portfolio and on the bank capital levels (Hosono et al., 2016; Schüwer et al., 2019). Areas with more severe commercial damages are more likely to reduce the lending capacity, especially for small lenders which lack access to geographically diversified markets (Neely and Wheelock, 1997). This suggests that markets with higher prevalence of small-bank credit can be subject to higher supply disruptions.

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.[19] Local lenders may not be affected by the worsening of asymmetric information but may have

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

[19] 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).

limited capacity to expand supply if the quality of the existing portfolio suffers.

## Descriptive Evidence

I start with some descriptive evidence for the role of local lenders during the hurricane recovery. Comparing counties with and without commercial losses, Table 1 shows that employment at the average industry grows at 0.13% without versus -0.65% with firm losses. Smaller firms take the brunt and contract by 1.22% during the first quarter.[20] Figure 1 plots the dynamic effect of commercial losses on jobs growth by comparing counties with more than 0.5% in losses to the rest. The run-up is similar but counties with higher damage see a higher impact during the month of landfall which persists for a couple of months.

Splitting the affected counties by the prevalence of local lenders shows that average growth with above-average local finance is higher during the month and the quarter of the landfall. The difference is about 0.3% and 0.15%, respectively. Figure 2 confirms this by distinguishing the recovery of counties with more than 0.5% in commercial losses by prevalence of local finance. Counties with lower local finance contract by 2.5% on impact and have a marginal recovery, compared to 1.6% and a stronger recovery for those with higher finance. The descriptive evidence suggests that counties where community banks play a more dominant role recover more quickly, with lower initial job loss and faster growth afterwards.

## Empirical Methodology

The descriptive evidence suggests that the majority of the labor impact occurs within the first quarter of the landfall. This is also consistent with other studies of the impact of natural hazards, such as Strobl (2011) and Cortés and Strahan (2017). Following this, my empirical analysis focuses on the three months before and after the impact. I estimate the average

[20] Hurricanes increase local churn within affected counties which leads to higher growth at young firms. Consistent with evidence that the labor impact is transitory (Ewing and Kruse, 2005), counties recover fairly quickly – quarterly growth is higher than the growth in the landfall month.

impact of local finance with the following model:

$$\begin{aligned}\text{EmpGrowth}_{c,i,t} = \;&\beta \text{HurricaneLoss}_{c,t} + \psi \text{HurricaneLoss}_{c,t} \times \text{LocalFinance}_{c,t} \\ &+ \gamma \text{LocalFinance}_{c,t} + \kappa Z_{c,i,t} + \alpha_{c,i} + \gamma_{i,s,t} + \epsilon_{c,i,t}\end{aligned} \tag{1}$$

using monthly observations of employment growth, $\text{EmpGrowth}_{c,i,t}$, for industry $i$ in county $c$ during month $t$. The sample covers a subset of industries during the short pre- and post-period for counties with commercial damage. $\text{HurricaneLoss}_{c,t}$ is equal to the commercial loss of the affected county $c$ for the months after the landfall and is equal to 0 for the months before. $\text{LocalFinance}_{c,t}$ measures the prevalence of local finance in county $c$ during month $t$, which is proxied by the fraction of community-bank deposits twelve month prior.

The first coefficients of interest, $\beta$ reflects the marginal impact of higher business loss on the post-landfall monthly jobs growth across all industries in the counties with zero local finance. The second coefficient, $\psi$, is a quasi-difference-in-difference term that reflects how the marginal impact of business loss varies with an increase in the prevalence of local finance.

I saturate the model with an extensive set of fixed effects (FE) and control variables which account for invariant differences in county-industry growth and time-varying demand shocks affecting each industry across counties in the same state. Industry by county FE, $\alpha_{c,i}$, control for the average jobs growth of industry $i$ in county $c$ during the period before and after the hurricane.

I allow for two types of industry-specific demand shocks. First, industry by state by year FE, $\gamma_{i,s,t}$, account for monthly difference in jobs growth of industry $i$ that are common to all other counties in the same state $s$. This partials out common trends in the growth of $i$ and for demand shocks across all other counties in the state. In the spirit of a diff-in-diff strategy, this approach compares the effect of commercial loss on industry-specific jobs growth across all state counties and tests whether it depends on local finance. Second, I add FE which partial out shocks common to $i$ across counties where $i$'s output is in the same state quartile or decile. In the diff-in-diff spirit, this only compares growth across counties where $i$ has similar output within the state. Because loss is county- and not industry-specific, comparing counties with similar sectoral output makes sure that hurricanes have the same impact.[21]

Control variables, $Z_{c,i,t}$, include a set of county-specific measures: household damage, population displacement, and the 12-month-lag of county industry HHI. These control for the effect of hurricane landfall on residents, which can impact employment as discussed above. I include county industrial concentration to account fo the resilience of the local labor market. I expect that diversified counties have more stable demand due to cross-industry linkages.[22] Additionally, I include the following county-industry specific measures from the preceding year: log output, log labor productivity, and fractions employed by small or less-than-3-year-old businesses.[23] These make sure that the impact of commercial loss and access to finance do not reflect underlying differences in the local industry characteristics.

A key identification concern is that the banking structure may be correlated with commercial loss, i.e. that counties with higher local finance are more or less vulnerable to losses. This issue appears to be minimal based on the comparison of counties with different prevalence of local finance in Table 1. Above- and below-median local finance counties have similar commercial and residential losses, and share the similar other economic characteristics. Additionally, my identification strategy compares county-industries with similar relative size. If historical hurricanes limit the size of industries which are sensitive to natural hazards, this comparison implicitly compares county-industries that are subject to similar risk of sever-weather, proxied by industry size.[24]

[21]For example, the same county loss can affect industry employment much less where there are a few firms compared to where the majority of the firms in the state are located. The second type of FE makes sure that I am comparing the impact across counties where the industry has a similar size and the impact is similar.

[22]This point was made in Kroll et al. (1991).

[23]Following Stansbury and Summers (2017), labor productivity is measured by the log of average weekly wages from BLS. Using total output divided by total employment does not change the main results. I use the wage as a measure of productivity since it is available each quarter, while GDP is only available annually. In sectors and counties with more significant seasonal employment variation, a measure based on GDP will overestimate productivity.

[24]For example, the size of the hospitality sector may be higher in places with exposure to weather shocks because coastal proximity is a key amenity in this industry. The opposite is likely to be true for manufacturing. There can be a concern that county-industries may be stuck in a path-dependent "bar" equilibrium, where industries sensitive to sever weather have not yet been impacted by significant hurricanes. Boustan et al. (2020) suggest that this is unlikely.

## Estimation Results

I start by discussing estimates for the average industry in the sample and further narrow down to specific sectors and firms of different size.

### Local Finance and the Recovery of the Average Industry

Estimates based on monthly employment growth across all industries in the sample are listed in Table 4. Starting with column (1), which includes county-industry FE, we see that higher business damage reduces employment growth at the average industry in the three months after the landfall. The interaction with local finance is positive, suggesting that counties with higher prevalence of community banks have smaller reductions. The bottom panel of the table lists estimates of the total effect at three levels of local finance. A 1%-loss-event reduces growth by 0.24% at low-finance counties.[25] At counties with median local finance jobs growth falls by 0.15%. Finally, in high-finance counties the reduction is very limited – 0.01%, and not statistically significant. The estimates are similar in column (2), which adds controls for the industry characteristics in each county, suggesting that they are not correlated with the average commercial losses or prevalence of local finance at each county.

In column (3), I add state by industry by month FE, which allow for common job growth changes for all counties in the same state in a given month. This can be an important source of variation for an industry during the month of hurricane landfall or the following two months – both during the initial disruption and in the ensuing recovery. The estimated coefficients are slightly smaller. The implied effect of 1% commercial loss in the county similarly depends on the prevalence of local finance. Job growth falls by 0.22%, 0.13%, and 0.003% with low to high local finance.

Estimates in columns (4) and (5) extend the specification in column (3) by accounting for common monthly shocks to sectoral job growth for counties where the sector's GDP is in the same state quartile or decile. There are two reasons why allowing for demand shocks

[25] This is a significant increase amounting to about one standard deviation of employment growth.

by relative industry size affects the estimated coefficients. First, as discussed above, county-level losses may not represent similar magnitude of impact for counties where the industry has different size. Second, industries of different size can vary in terms of how quickly they can restore capacity. My results appear to not be substantially sensitive to either of the two factors. Estimates in column (5) suggest that local lenders substantially improve the recovery after landfall, with reductions in job growth ranging from 0.25% (no local finance) to 0.15% (median finance). Counties with high local finance see slightly positive but not statistically significant job growth. This implies that high presence of community banks is associated with a full recovery after a range of possible damages to local businesses.

Moving to the effect of hurricanes on local population, residential loss has a negative and marginally significant effect, consistent with findings that wealth shocks depress activity even with minimal business loss (Xiao and Van Zandt, 2012; Gallagher et al., 2019). The effect of population displacement is negative but only significant in the sample of costlier events, where a bigger portion of the county's population may be relocated.

**Impact on Small Businesses**

Substantial evidence documents that natural disasters exert a disproportionate impact on smaller firms. For example, Basker and Miranda (2018) finds that they are much more likely to permanently shut down. Collier et al. (2020) also argue that smaller firms are likely to face more severe financial challenges after hurricanes and bear most of the cost of such events. Small firms are more vulnerable because they often do not undertake preparedness or mitigation measures, have lower cash reserves, and are exposed to supplier disruptions Dahlhamer and Tierney (1998).

To the extent that community banks can leverage their information advantage and provide credit to firms that may be too risky after a hurricane landfall, counties with more local finance should experience faster recovery. I test this hypothesis by focusing on this subset of firms with two measures: total establishments and employment in firms with less than twenty employees. Since variation in establishments is dominated by changes in units with lower number of employees, this measures can reflect the impact on smaller firms. However, this can underestimate the impact if firms limit employment but remain operational. This is why I also examine the effect on employment at smaller firms.[26] Note that both measures are reported quarterly and my estimates reflect the effect at the end of the quarter of landfall.

Column (1) of Table 5 reports that prevalence of local lenders is associated with faster jobs growth after a landfall. The direct effect of firm loss is not significant, which leads to the total effect at different levels of local finance not being statistically significant. This suggests that local finance does not help with business closure since firms can reduce employment and avoid closing establishments even when the prevalence to local lenders is low. The effect of finance is stronger when looking at employment of small firms. The estimates in column (2) imply that recovery is improved with more community banks. 1% business losses reduce jobs growth by 0.95% and 0.65% with low or with median local finance. In counties with high finance, employment growth falls by 0.19% and the effect is not statistically significant. The 0.95% contraction is economically significant since it is close to one standard deviation.

### Impact on Individual Sectors

The sector-specific impact of hurricanes is widely documented. Meltzer et al. (2021) shows that the retail sector, which relies on local foot traffic, saw a 14% reduction in employment in NYC after hurricane Sandy. The differential impact by industry is emphasized by Belasen and Polachek (2008) and is documented as early as in Guimaraes et al. (1993).

Columns (3) through (7) of Table 5 focus on the outcomes at individual sectors. The interaction between damage and local finance is remarkably consistent within each. Trade, Transportation, and Utilities is most severely affected and, in this sector, local finance reduces jobs contractions but does not completely eliminate them. Employment growth falls by 0.1% even in counties with community banks play an important role. This is consistent with the

[26] For both measures there is no way to determine if these are part of a multi-unit franchise. Basker and Miranda (2018) documents that franchises tend to do better than single-unit firms.

strong decline in jobs that is documented in the literature. My results suggest that even though hurricanes strongly reduce employment in this sector, areas where local finance plays a bigger role are more resilient.

I find that Manufacturing employment is not affected. This further highlights the fact that reliance on foot traffic and needing a store front are important factors that lead to contractions after commercial losses. Finally, local finance has the strongest positive effect in the case of Professional services, followed by Hospitality, and Other Services.

All together, the evidence consistently shows that local finance mitigates hurricane-driven job contractions. This is the case for the average industry, for most individual sectors, and is pronounced for small businesses. In the robustness section, I also show that local finance matters similarly when damages are substantial and with less costly hurricanes. My evidence suggest that in counties where local banks play an important role funding disruptions are limited, resulting in limited employment contractions and faster recovery. Counties with more distant or national banks do not appear to have a similarly positive effect. As a result, differences in local banking structure can lead to substantial variation in the employment after hurricanes.

# 5 Why Community Banks Help with Recovery?

Single-market lenders have an ambiguous theoretical impact on local economic conditions, depending on the strength of demand and supply shocks (Keeton et al., 2009).[27] They amplify contractions if portfolio losses disproportionately reduce their credit supply, or limit them if borrowers become riskier, which disproportionately reduces demand faced by non-local lenders. The volatility-reducing effect of local lenders is surprising and raises questions about the systemic impact of hurricanes on the financial condition of single-market lenders. On one side, if information asymmetry becomes severe after landfall and causes non-local

[27] In principle, they can increase volatility if shocks affect the supply of credit or reduce volatility if demand for funds is affected (Morgan et al., 2004).

lenders to significantly reduce lending, the financial state of local lenders will likely not significantly change the relative amount of credit as a function of local finance – even local lenders with sizable portfolio losses can provide relatively more credit due to limited access to other markets. On the other hand, if information asymmetry increases only modestly, the positive effect of local finance requires that the lending capacity of local lenders is not affected – local lenders with sizable shocks to capital will offset their information advantage. In other words, local lenders improve economic resilience because of a combination of heightened information frictions and ability to avoid portfolio losses. To shed further light, I examine the extent to which hurricanes impact the lending capacity of small banks and the relevance of information frictions after the landfall. I do this by relying on a triple-difference identification strategy based on the employment data and by directly investigating how local banks are affected. I discuss each approach in what follows.

## Empirical Methodology

There is limited evidence about the importance of supply shocks affecting lenders after hurricanes (Klomp, 2014). Local lenders are more likely to experience reductions in capital or funding after hurricanes due to their geographic concentration (Brei et al., 2019; Hosono et al., 2016). However, they can offset higher local exposure by relying on the efficiency of monitoring or screening informationally-intensive businesses at close distance.[28] The proprietary information collected over time generates rents and protects borrowers from credit disruptions by allowing lenders to maintain higher capital levels (Bolton et al., 2016).[29]

The information frictions impact of natural hazards is less controversial. Losses exacerbate frictions by destroying collateral and increasing risk of new lending (Berg and Schrader,

[28]For example, see Acharya et al. (2006); Hayden et al. (2007); Tabak et al. (2011).

[29]Alternatively, local lenders may internalize the adverse effects of not extending additional credit which can have spillover effects to the rest of the local economy and further deteriorate the bank's portfolio of loans (Favara and Giannetti, 2017; Giannetti and Saidi, 2019). Initial shocks from the hurricane can be magnified as they ripple through the local economy, leading to further impairment of the value of existing loans or disruption of future business. Since local lenders are concentrated in a single market, they can internalize this spillover and support recovery despite the reduction in the quality of its portfolio in order to prevent future deteriorations. This can limit the importance of the supply effect.

2012). The increase in asymmetric information constitutes a negative demand shock which can have a smaller effect on local lenders with higher informational advantage due to specialization in a given market (Paravisini et al., 2015), higher market power (Duqi et al., 2021), or reliance on relationship lending Agarwal and Hauswald (2010).

The reliance on soft information by local lenders results in an information advantage, limiting the impact of demand shocks after hurricanes, and can lead to more prudent lending, which also insulates from supply shocks after landfall. This provides a challenge for the independent identification of supply from demand shocks. I overcome this with two separate approaches. First, I exploit pre-hurricane differences in the concentration and productivity of local economies and use a triple-difference specification to quantify the importance of each shock. Second, I use bank data to focus on local lenders with similar information advantage but different exposure to systemic risk after hurricanes due to their different size. I compare outcomes depending on bank size in order to quantify the importance of supply shocks.

### Employment Model Specification

I estimate the following extension of the baseline model:

$$\begin{aligned}
\mathrm{EmpGrowth}_{c,i,t} = {} & \beta \mathrm{HurricaneLoss}_{c,t} + \psi \mathrm{HurricaneLoss}_{c,t} \times \mathrm{LocalFinance}_{c,t} \\
& + \eta \mathrm{HurricaneLoss}_{c,t} \times \mathrm{LocalFinance}_{c,t} \times \mathrm{X}_{c,t} \\
& + \gamma \mathrm{LocalFinance}_{c,t} + \gamma_2 \mathrm{X}_{c,t} + \psi_2 \mathrm{HurricaneLoss}_{c,t} \times \mathrm{X}_{c,t} \\
& + \gamma_3 \mathrm{LocalFinance}_{c,t} \times \mathrm{X}_{c,t} + \kappa Z_{c,i,t} + \alpha_{c,i} + \gamma_{i,t} + \epsilon_{c,i,t}
\end{aligned} \tag{2}$$

$\mathrm{X}_{c,t}$ is an indicator variable that takes a value of one in counties with higher concentration or in county-industries with higher productivity.[30] Productivity is based on industry-county-specific earning and the indicator is set to one for above state-median values. The first measure of concentration reflects the county diversity in industrial output based on the HHI index of output shares. I set to one all counties with above-median values for the state. The second measure of concentration reflects the spatial clustering of activity based on the share of employment in each census tract. I identify counties where activity is clustered in one

[30] Each indicator variable is based on the twelve-month lag values.

tract by comparing jobs in the top tract to employment under uniform distribution. I set to one counties where the top tract jobs are over three times more.

This model uses a triple-difference to estimate how the positive effect of local finance varies depending on local firm productivity and the extent to which hurricanes affect local systemic risk.[31] $\eta$ captures the local-finance effect heterogeneity along each dimension, identified by comparing counties with the same commercial loss and prevalence of local finance but with different sectoral productivity, industrial, or geographic concentration.[32] Crucially, in all cases, the direct impact of productivity and concentration on jobs recovery is captured by $\psi_2$. The coefficient of interest, $\eta$, identifies how local finance affects growth across markets with different productivity or concentration, after taking into account how each of the two directly impacts recovery after commercial losses.

First, I focus on pre-existing differences in industry productivity across affected counties. I assume that asymmetric information is more acute in markets with less productive firms. $\eta$ compares the effect of local finance on jobs growth across markets with different information frictions. Increase in the risk after landfall affects loan demand and make new loans are less profitable. Since non-local lenders have access to other markets, demand shocks limit additional lending and exacerbate job contractions. A negative estimate for $\eta$ suggests that local finance has a smaller effect in county-industries with high-productivity firms, for which lending risk is likely to increase less after the landfall. This is evidence that demand shocks play a key role in explaining the effect of local finance.

Second, I exploit the pre-existing differences in the geographic and industrial concentration of local economies, in order to examine if supply shocks play an important role for the positive effect of local lenders. Landfall in economies where activity is concentrated in one census tract or one industry can lead to highly correlated local commercial losses and can increase systemic portfolio risk. Even lenders that rely heavily on proprietary soft information

[31]Systemic risk refers to the probability of default that is common to all borrowers in a given market.

[32]Note that the direct effect of productivity or concentration is reflected by $\psi_2$. This means that $\eta$ reflects the impact of local finance in after controlling for the response of counties with different productivity or concentration.

can be exposed to such systemic risk and experience correlated loan defaults that reduced supply. $\eta$ compares the effect of local finance across markets with different systemic risk and tests whether supply shocks in more concentrated markets limit the ability of local lenders to support economic recovery. A small and insignificant estimate will further support the information-advantage story, suggesting that even local lenders with higher supply shocks provide relatively more credit than non-local banks. A sizable negative estimate supports the interpretation that demand shocks are less important and local lenders improve resilience only when they avoid portfolio losses.

**Community Bank Model Specification**

To provide more direct evidence for the effect of supply shocks after hurricanes, I estimate the following model with quarterly data on bank lending and portfolio quality, focusing on the two quarters before and the quarter of a hurricane:

$$Y_{b,c,q} = \beta \text{HurricaneLoss}_{c,q} \times \text{Small}_{b,(q-4)} + \gamma W_{b,q-4} + \alpha_b + \lambda_{c,q} + \epsilon_{b,c,q} \tag{3}$$

where $Y_{b,c,q}$ stands for performance and lending measures for bank $b$, with a home in county $c$, during quarter $q$. The sample includes only home banks, i.e. only lenders in the county where they have more than 65% of deposits.[33] Emmons et al. (2004) and Yeager (2004) argue that very small lenders face more idiosyncratic risk and are not systemically impacted by local economic conditions, because they have higher exposure to individual borrowers as opposed to systemic market factors. This suggests that while home banks within the same county are local and have similar information advantage, they face different supply shocks after a hurricane depending on their relative size. The empirical model exploits this variation in order to identify the role of supply shocks in the response of local lenders. I classify lenders with less than \$300M in assets as small, following evidence form Wheelock and Wilson (2001)

[33]I further exclude lenders that are: part of a multi-bank holding company, non-community as defined by FDIC, owned by non-bank-holding-company, transformed during/two quarters prior the sample. Following Schüwer et al. (2019), I also drop banks with less than 50% deposit share, 50% loan share, no business loans, less than 8%/more than 40% Tier2 Capital Ratio.

that above this size lenders achieve sufficient diversification of idiosyncratic risk and are more sensitive to systemic market conditions.

The coefficient of interest, $\beta$, reflects the difference in performance and lending at smaller lenders during the quarter after the hurricane landfall. A positive estimate suggests that really small lenders face lower supply shocks and are in position to expand credit and support recovery. Conversely, it implies that hurricanes increase systemic risk, which reduces the supply of credit mostly for bigger local lenders whose size makes them more susceptible to the local economic conditions.

I saturate the model with a bank FE, $\alpha_b$, and county-quarter FE, $\lambda_{c,q}$, and bank control variables in $W_{b,q-4}$.[34] County-quarter FE controls, non-parametrically, for a common county-level shocks that affects all lenders in a county, including a change in the credit demand. This allows me to identify the response relative to the big banks and helps distinguish whether smaller lenders have smaller losses and expand lending after hurricanes.

The bank-level impact provides additional evidence for the relationship between size and market risk exposure. Bigger lenders diversify individual-default risk, increasing local-market risk exposure, while smaller ones have higher idiosyncratic risk (Yeager, 2004). I explore the variation in idiosyncratic risk by size and assume that credit demand *within the county* is not size-dependent.[35] I use within-county variation to test whether local banks improve recovery because they are less exposed to market-level risk and the average smaller bank has limited losses. This is not to say that community banks are not affected by weather events but that the average small banks has better loan portfolio quality due to the lower market risk.

## Estimation Results

**County-Industry Model Results:** Table 6 lists the estimates from model 2 and adds in column (1) the baseline results from the previous section. Results in column (2) suggest that

[34] $W_{b,q-4}$ includes: log assets, log deposits, log unused loan commitments, risk-based capital ratio, share of non-performing loans, share of business loans, and net income before extra items over loans.

[35] The sample includes smaller independent banks with the majority of deposits within the same county.

the effect of local finance varies by county-industry productivity. Surprisingly, local finance does not improve recovery in markets with less productive firms, where the information advantage is expected to be stronger. This suggests that local and non-local lenders might be similarly impacted by the increase in borrower risk.[36] The effect of local finance is significantly stronger when firms are more productive. A 1%-loss-event reduces employment by 0.14%/0.06% at low/high finance compared to 0.4%/0.02% in high-productivity counties. Since more productive markets are expected to suffer less from information frictions, the evidence suggests that demand shocks play are limited role in explaining the positive effect of local finance.[37] If local lenders are likely to suffer lower supply shocks in markets with more productive firms, the results can suggest that supply shocks – or the lack thereof, can explain the positive effect of local finance.

Results in column (3), based on industrial concentration, suggest that local finance has a stronger effect in diversified counties. Counties with low prevalence of local finance contract by 0.3% regardless of diversification but increasing local finance from the 25th to the 50th percentile limits the contraction by half at diversified counties and by less than a third elsewhere. Since local lenders have similar information advantage in both types of markets, the fact that local finance does not similarly improve job recovery implies that supply shocks are more important than demand shocks. If local lenders in counties with a range of industries are less exposed to market risk and have lower average delinquencies, they can provide funding to firms with disruptions after a hurricane.

The results in column (4), which focus on spatial concentration of activity, closely mirror the case with industrial concentration. Clustering of activity leads to correlated losses that can reduce local banks' lending capacity and limit the effect of local finance. According

[36]Keeton et al. (2009) suggests that local lenders can focus on other assets and invest in securities instead of loans.

[37]The fact that the difference is much higher at higher productivity economies can only be indicative of demand effects if non-local lenders limit lending to all firms affected by hurricanes, due to the increase in riskiness for all firms. This is consistent with evidence by Presbitero et al. (2014) which shows that distant lenders have home bias and are more likely to reduce credit even to healthy/large firms. In other words, asymmetric information must become so severe after hurricanes that it causes non-local lenders to reduce lending even in markets where firms have higher productivity.

to the results, local finance has a stronger effect when activity is dispersed and portfolio losses are less correlated. I find that in counties with more evenly dispersed activity, moving from the 25th to the 50th percentile of access reduces contractions by a third compared to a quarter elsewhere. I control for the direct effect of spatial concentration on recoveries, which is reflected in the lower effect of loss at concentrated counties for any finance level, due to the fact that hurricanes generate higher average loss in counties with dispersed activity.

Column (5) adds all three indicators, leaving estimates unchanged, suggesting that productivity and concentration capture a distinct factor that explains the local finance mechanism. The estimates at the bottom focus on the effect of local finance across counties with different productivity but with low industrial and geographic concentration. With limited systemic risk due to lower concentration, local lenders face lower supply shocks and are able to improve the recovery event in markets with less productive firms. It appears that the effect is much stronger when systemic risk is limited, suggesting that supply shocks are a key driver behind the role of local finance.

**Community Bank Model Results:** Table 7 reports results from the analysis of bank outcomes. Columns (1)-(7) include county by quarter FE, where I identify the impact of hurricanes on small lenders relative to the rest that operate in the same county. Columns (8)-(14) include county GDP state quartile by quarter, where I compare bank outcomes across counties with similar output and can estimate the effect for small and bigger lenders.

The results in columns (1)-(4) and (8)-(11) highlight the difference in the way hurricanes affect the loan portfolio of banks which are concentrated in one home county but vary in size and, as a result, have different exposure to systemic market risk. Since all banks in the sample are concentrated in one county, they should benefit from the same efficiency of monitoring and screening of opaque businesses, and develop similar information advantage. This ensures that any performance differences are not due to asymmetric information post hurricane. The evidence in column (1), based on the loan-loss-allowance ratio, suggests that small lenders face lower defaults after hurricanes. A 1%-loss event is associated with 5 bp lower ratio, or 10% of the standard deviation, compared to bigger lenders. The results in column (8), where I can estimate the effects for both bank sizes, show that risk rises much less at smaller banks after a landfall. Estimates in columns (2) and (3) confirm that small banks remain more profitable: a 1% event is associated with 0.5% faster net interest income growth and 0.1% higher net income over loans.[38] Columns (9) and (10) suggest that this is due to the relatively smaller decline in profitability at smaller lenders. Columns (4) and (11) present evidence that bigger lenders have lower capital levels after landfalls.

Examining growth of total, commercial and industrial (CI) loans, and personal loans, in (5)-(7), I find that the deterioration in the loan portfolio of bigger banks can limit new credit (Schwert, 2018).[39] Across the board, smaller lender are able to expand credit much faster in the quarter after the hurricane. At smaller banks, a 1% event is associated with 0.3% faster growth in total loans, 1% faster growth in CI loans, and 3% faster growth in loans to individuals at smaller banks.

The evidence points to consistent quality and origination differences by bank size after the hurricane. Both small and bigger lenders are located in the same county, but the relative size makes the bigger ones more exposed to local market risk (Emmons et al., 2004) and increases the odds of direct loan loss. Smaller banks face more idiosyncratic risk, which either wipes out the portfolio or leaves them unaffected. The evidence indicates that the average small bank has lower direct loss and expands lending post hurricane.

## Discussion

The two sets of evidence in this section point to two main factors working together to explain the baseline results. First, my evidence suggests that demand shocks across local and non-local lenders play a smaller role in explaining the beneficial effect of local finance. I expected that local lenders are more likely to rely on proprietary information and experience

[38] 0.5% higher net interest income growth represents about 10% of the standard deviation and 0.1% of higher net income over loans represents about a third of the standard deviation for this outcome.

[39] Results, not reported, using loans secured by commercial RE and total loans secured by RE are very similar.

limited demand shocks due to higher information friction and borrower risk after hurricanes. However, my results suggest that local lenders improve the recovery for firms with higher productivity, which are less likely to be subject to higher information frictions. Furthermore, after controlling for supply shocks, I find that local finance has a similar effect on the employment of low- and high-productivity firms.

Second, my evidence strongly suggests that the positive effect of local finance is explained by the limited supply effects that hurricanes can have on small lenders. Both employment and bank results indicate that local banks are able to avoid significant losses to their loan portfolio and maintain capacity to expand lending. I show that local lenders limit employment contractions more in counties with higher industrial or geographic diversification. Such places are unlikely to experience uniform business damages either because industries vary in their vulnerability to hurricanes or since businesses are not clustered in the same location. As a result of their smaller size and primary exposure to idiosyncratic risk, a subset of community banks remains unaffected in terms of quality of the loan portfolio and can provide funding for repairs. I provide direct evidence of this by comparing the lending and performance of local banks with different exposure to market risk within affected counties. I find that bigger banks experience higher risk of loan defaults and do not expand lending, while smaller ones expand credit and see less of an effect on their loan performance.

# 6 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 two alternative classifications of local lenders: at least 90% of a bank's deposits are located in the same county; all of the bank's deposits are in the same county. Each of the two 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. I estimate specification 4 with total employment, employment for small firms (less than 20 employees), and the Trade/Transportation/Utilities sector. The results are presented in Table 8. Estimates are statistically significant and within a third of the baseline estimates. For each of the three outcome variables, restricting the definition of a local lender reduces the direct impact of business damages and its interaction with local finance. Since the direct effect of damages, capturing the impact with no access to finance, now includes some counties with local lenders, the estimate is expected to be lower. The same holds for the interaction term. Overall, the evidence implies that the definition of community lenders does not play a critical role in identifying the effect of access to local finance during hurricane recovery.

**Block-buster Hurricanes**

I distinguish the overall severity of a hurricane by adding up business losses for each state and assume that losses over $1 billion represent block-buster events. Results in column (6) of Table 4 , which presents estimates for severe hurricanes, suggest that community banks are effective at alleviating job contractions even when losses are substantial. The estimated impact of finance closely matches that of the full sample, implying that the baseline estimates rely on variation from severe events.

Local finance appears to have a beneficial effect on the local economy even for less severe events. The estimates in Column (7) have the expected signs but are much higher in magnitude. The results suggest that the job impact of less severe events is proportionately higher. At the same time the average commercial loss is lower, leading to a smaller overall impact.

**Alternative Measures of Access to Local Finance**

Columns (8) through (10) of Table 4 use alternative specifications of prevalence of local finance. I experiment with the log of local deposits, the fraction of local banks, and the log of local lenders. The first two measures produce similar results. The log of local lenders does not have a beneficial impact on recovery. This suggests that local economies where small lenders play an important role in providing local credit benefit from the higher access after landfall. The availability of local lenders by itself does not improve recovery. In other words, the prevalence and not access to local finance appears to play a key role.

# 7 Conclusion

In this paper, I consider if un-diversified lenders mitigate the negative employment shocks associated with hurricane damage to firms in specific industries, with novel data about the commercial losses due to 33 hurricanes during 1999-2019. The evidence, which is based on a quasi diff-in-diff model of monthly industry jobs growth in counties with commercial loss, consistently shows that access to local finance dampens the employment contractions. This applies to the average industry in affected counties, to most individual sectors, and has a particularly strong effect on small businesses.

I provide new evidence about the necessary conditions allowing lenders to assist in the recovery. I rely on two different samples – based on employment and bank data, and document that the volatility-reducing role of local lenders is more sensitive to their supply conditions than to the information frictions after a landfall. Because local lenders limit employment contractions more in counties with higher industrial or geographic diversification – where they are unlikely to experience systemic portfolio losses, it appears that un-diversified lenders improve resilience only when they avoid direct portfolio losses. I find support for this in the bank data which suggests that there is a difference in the way hurricanes affect the loan portfolio of banks which are concentrated in one home county but vary in size and, as a result, have different exposure to systemic market risk. I find that bigger banks experience higher risk of loan defaults and do not expand lending, while smaller ones see less of an effect on their loan performance and expand credit. As a result of their smaller size and primary exposure to idiosyncratic risk, a subset of community banks remains unaffected in terms of quality of the loan portfolio and can provide funding for repairs.

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# Tables and Figures

Table 1: Summary Statistics for Counties Affected by Hurricanes

This table lists summary statistics at the county level for states with hurricanes. Hurricanes are based on major disaster declarations by FEMA between 1999 and 2019 (33 in total). Business loss consists of SBA's business loans, FEMA's public assistance grants, and flood insurance payments related to non-residential buildings. Residential loss consists of SBA's homeowners loss, FEMA's IHP loss, and flood insurance payments related to residential buildings. Counties are divided into groups based on business loss and access to local finance. The group with no (positive) business damage, Bus Damage=0 (Bus Damage>0), lists monthly average and standard deviation during the impact month for counties with no (positive) business impact. The last four columns divide the counties with a positive business damage based on the median of the fraction of local deposits in the county. Disaster loan shares are based on a loan-level information with 6-digit NAICS information for 13 hurricanes between 2002 and 2012. Economic data for employment comes from the Bureau of Labor Statistics; data for shares of less-than-20-workers/3-or-less-years-old come from the Quarterly Workforce Indicators; output data comes from the Bureau of Economic Analysis; banking sector data comes from FDIC. Data is listed as percentages but is utilized in non-percentage form in the rest of the paper.

| | Bus Damage=0 | | Bus Damage>0 | | Bus Damage>0 LocDep<Median | | Bus Damage>0 LocDep>Median | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | mean | sd | mean | sd | mean | sd | mean | sd |
| **HurricaneDamage** | | | | | | | | |
| Total Business Damage in $1,000 | 0 | 0 | 23,918 | 261,983 | 20,050 | 134,195 | 27,766 | 344,990 |
| Total Residential Damage in $1,000 | 0.278 | 13.24 | 28,603 | 246,074 | 31,079 | 278,408 | 26,139 | 209,085 |
| Relative Business Damage in % | 0 | 0 | 0.633 | 3.632 | 0.665 | 3.992 | 0.601 | 3.236 |
| Relative Residential Damage in % | 0 | 0.00217 | 0.853 | 4.311 | 0.854 | 4.175 | 0.852 | 4.444 |
| Total Business Damage SBA in $1,000 | 0 | 0 | 7,984 | 72,734 | 7,883 | 63,358 | 8,084 | 81,016 |
| Total Business Damage Flood Insurance in $1,000 | 0 | 0 | 1,412 | 11,230 | 1,404 | 12,312 | 1,419 | 10,043 |
| Total Public Damage in $1,000 | 0 | 0 | 14,522 | 232,203 | 10,763 | 79,951 | 18,263 | 318,131 |
| Total Residential Damage SBA in $1,000 | 0.113 | 6.409 | 12,425 | 97,951 | 12,879 | 99,715 | 11,974 | 96,200 |
| Total Residential Damage Flood Insurance in $1,000 | 0.0764 | 5.625 | 11,765 | 132,594 | 14,069 | 166,709 | 9,473 | 86,179 |
| Total Residential Damage FEMA in $1,000 | 0.0880 | 4.088 | 4,412 | 33,073 | 4,130 | 28,591 | 4,692 | 37,004 |
| **Economy** | | | | | | | | |
| Population in 1,000 | 112.5 | 267.5 | 145.9 | 305.2 | 157.0 | 317.5 | 134.8 | 292.2 |
| Log County GDP | 13.72 | 1.611 | 14.03 | 1.655 | 14.06 | 1.727 | 14.00 | 1.581 |
| County GDP per Worker | 148.3 | 492.5 | 107.3 | 62.76 | 107.9 | 50.28 | 106.6 | 73.07 |
| Average Weekly Wages in $1,000 | 0.619 | 0.188 | 0.642 | 0.196 | 0.657 | 0.193 | 0.626 | 0.197 |
| County Employment in 1,000 | 39.60 | 117.8 | 51.32 | 131.3 | 53.16 | 120.7 | 49.50 | 140.9 |
| Growth Rate County Employment in % (month of impact) | 0.131 | 3.068 | -0.647 | 2.909 | -0.800 | 3.028 | -0.496 | 2.779 |
| Growth Rate County Employment in % (quarter of impact) | 0.142 | 3.057 | -0.193 | 3.078 | -0.269 | 3.158 | -0.116 | 2.993 |
| Growth Rate County Employment 20-less Establishment in % | 0.275 | 9.419 | -1.223 | 7.188 | -1.343 | 7.514 | -1.116 | 6.884 |
| Growth Rate County Employment 3-less-year-old Establishment in % | 0.480 | 35.48 | 0.920 | 30.35 | 0.501 | 34.67 | 1.290 | 25.94 |
| Share in 20-or-less-worker Establishments in % | 27.33 | 11.20 | 26.39 | 9.478 | 26.79 | 10.66 | 25.98 | 8.112 |
| Share in 3-or-less-year-old Establishments in % | 7.700 | 4.449 | 8.143 | 4.224 | 7.779 | 4.148 | 8.507 | 4.270 |
| County Industry HHI (GDP based) | 76.16 | 14.18 | 78.64 | 9.444 | 78.88 | 9.184 | 78.39 | 9.693 |
| **BankingSector** | | | | | | | | |
| Local Banks | 1.737 | 3.234 | 1.994 | 3.464 | 0.964 | 2.287 | 3.024 | 4.080 |
| Non-Local Banks | 6.866 | 6.877 | 7.998 | 7.592 | 8.977 | 7.923 | 7.020 | 7.116 |
| Share of Local-bank Deposits in % | 25.93 | 29.11 | 23.22 | 26.55 | 2.534 | 4.228 | 43.90 | 23.15 |
| Share of Local banks in % | 20.97 | 23.36 | 19.17 | 20.42 | 4.756 | 8.107 | 33.57 | 18.78 |
| Log Local-bank Deposits | 7.944 | 5.846 | 8.198 | 5.942 | 3.974 | 5.775 | 12.42 | 1.275 |
| **Industries** | | | | | | | | |
| Employment share Manufacturing in % | 16.25 | 13.16 | 15.60 | 12.58 | 14.85 | 12.51 | 16.35 | 12.61 |
| Employment share Trade-Transportation-Utilities in % | 24.59 | 6.415 | 24.88 | 6.220 | 24.82 | 6.626 | 24.95 | 5.791 |
| Employment share Professional Services in % | 8.166 | 5.823 | 9.060 | 5.834 | 9.674 | 6.307 | 8.452 | 5.256 |
| Employment share Leisure and Hospitality in % | 11.73 | 6.490 | 12.25 | 6.600 | 12.58 | 6.686 | 11.92 | 6.500 |
| Employment share Other Services in % | 3.118 | 1.732 | 3.179 | 1.642 | 3.294 | 1.781 | 3.065 | 1.485 |
| Count | 39,679 | | 2,663 | | 1,328 | | 1,335 | |

## Table 2: County Damage by Hurricanes

This table lists summary statistics for counties impacted by specific hurricanes. The first five columns include counties with positive business damage; the last five columns include counties with positive residential damage. Some rows include multiple hurricanes because counties were hit by multiple events in the same month. Relative damage is in percentage form.

| | Relative Business Loss | | | | | Relative Residential Loss | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Hurricanes | N | mean | p75 | p90 | sd | N | mean | p75 | p90 | sd |
| ALEX | 20 | 0.114 | 0.113 | 0.257 | 0.178 | 10 | 0.0674 | 0.0633 | 0.239 | 0.113 |
| BARRY | 20 | 0.0192 | 0.0319 | 0.0439 | 0.0206 | 13 | 0.00722 | 0.0108 | 0.0114 | 0.00804 |
| BRET | 12 | 0.0276 | 0.0371 | 0.0639 | 0.0210 | 10 | 0.00276 | 0.00344 | 0.00795 | 0.00307 |
| CHARLEY | 55 | 1.179 | 0.0663 | 0.757 | 5.155 | 37 | 1.595 | 0.358 | 2.334 | 4.922 |
| CLAUDETTE | 18 | 0.201 | 0.328 | 0.543 | 0.187 | 18 | 0.178 | 0.262 | 0.406 | 0.166 |
| DENNIS | 164 | 0.321 | 0.136 | 0.667 | 1.080 | 95 | 0.614 | 0.569 | 1.591 | 1.468 |
| DOLLY | 11 | 0.193 | 0.182 | 0.811 | 0.368 | 7 | 0.276 | 0.825 | 0.929 | 0.417 |
| FLORENCE | 77 | 0.971 | 0.379 | 2.077 | 2.805 | 62 | 1.635 | 0.827 | 4.225 | 4.417 |
| FLOYD | 167 | 0.178 | 0.103 | 0.448 | 0.485 | 129 | 0.137 | 0.0580 | 0.483 | 0.389 |
| FRANCES | 91 | 0.0823 | 0.0781 | 0.188 | 0.164 | 26 | 0.0799 | 0.132 | 0.193 | 0.111 |
| FRANCES, IVAN | 37 | 1.638 | 1.235 | 4.128 | 3.536 | 32 | 3.520 | 1.248 | 2.960 | 12.67 |
| FRANCES, IVAN, JEANNE | 31 | 1.196 | 1.243 | 3.046 | 1.969 | 31 | 2.058 | 1.898 | 4.856 | 3.300 |
| FRANCES, JEANNE | 22 | 0.445 | 0.559 | 1.007 | 0.369 | 22 | 1.452 | 2.042 | 3.061 | 1.512 |
| GUSTAV | 80 | 0.238 | 0.284 | 0.724 | 0.405 | 51 | 0.596 | 1.086 | 1.617 | 0.792 |
| GUSTAV, IKE | 26 | 0.751 | 0.663 | 1.707 | 1.582 | 23 | 1.186 | 1.122 | 2.495 | 2.301 |
| HARVEY | 69 | 3.171 | 1.032 | 5.997 | 13.09 | 61 | 3.193 | 2.300 | 8.105 | 7.373 |
| HERMINE | 24 | 0.184 | 0.151 | 0.509 | 0.417 | 15 | 0.301 | 0.286 | 0.862 | 0.457 |
| IKE | 49 | 0.849 | 0.456 | 2.422 | 2.039 | 39 | 1.683 | 0.912 | 1.861 | 5.300 |
| IRENE | 203 | 0.356 | 0.163 | 0.468 | 1.528 | 181 | 0.521 | 0.171 | 0.533 | 2.701 |
| IRMA | 240 | 0.264 | 0.174 | 0.615 | 1.115 | 79 | 0.608 | 0.591 | 1.309 | 1.483 |
| ISAAC | 96 | 0.154 | 0.110 | 0.244 | 0.607 | 56 | 0.784 | 0.258 | 1.009 | 3.436 |
| ISABEL | 134 | 0.338 | 0.258 | 0.844 | 0.941 | 129 | 0.878 | 0.523 | 2.234 | 2.547 |
| ISIDORE | 26 | 0.0583 | 0.0783 | 0.159 | 0.0860 | 20 | 0.172 | 0.173 | 0.399 | 0.294 |
| IVAN | 188 | 0.188 | 0.130 | 0.327 | 0.744 | 152 | 0.576 | 0.399 | 1.476 | 1.572 |
| KATRINA | 171 | 2.011 | 0.394 | 3.437 | 7.004 | 119 | 4.787 | 2.449 | 10.38 | 12.91 |
| LILI | 39 | 0.156 | 0.197 | 0.594 | 0.231 | 37 | 0.215 | 0.272 | 0.504 | 0.318 |
| MATTHEW | 113 | 0.578 | 0.470 | 1.508 | 1.145 | 99 | 0.410 | 0.420 | 0.951 | 0.844 |
| MICHAEL | 118 | 1.936 | 0.377 | 2.794 | 7.723 | 53 | 2.614 | 1.639 | 5.634 | 7.133 |
| NATE | 12 | 0.0254 | 0.0385 | 0.0413 | 0.0379 | 4 | 0.0180 | 0.0239 | 0.0319 | 0.00941 |
| OPHELIA | 10 | 0.186 | 0.0568 | 0.851 | 0.428 | 8 | 0.125 | 0.189 | 0.510 | 0.174 |
| RITA | 136 | 0.772 | 0.123 | 1.045 | 4.190 | 68 | 3.676 | 3.137 | 13.03 | 9.836 |
| SANDY | 132 | 0.237 | 0.100 | 0.508 | 0.680 | 91 | 0.763 | 0.180 | 1.169 | 2.919 |
| WILMA | 20 | 0.929 | 1.089 | 1.602 | 1.838 | 19 | 1.499 | 0.827 | 3.760 | 4.018 |

# Table 3: Summary Statistics for Bank Sample

This table reports summary statistics for the sample of banks used in specification (3). The sample includes community banks used to calculate the Local Finance measure and excludes lenders that are part of a multi-bank holding company, are designated as non-community banks by FDIC, are owned by non-bank-holding-company, or have undergone any transformation during/two quarters before the sample. I also drop banks with less than 50% deposit share, 50% loan share, no business loans, less than 8%/more than 40% Tier2 Capital Ratio. I split the set of the remaining lenders based on asset-size cutoff of $300 mil. and designate those below the cutoff as small community banks. Unaffected (affected) are banks in counties with no (positive) business damage. The sample if based on quarterly observations of bank variables covering two quarters prior to a hurricane and on quarter after. Variables are listed in percentage form.

| | Unaffected | | Affected, Small | | Affected, Medium | |
|---|---|---|---|---|---|---|
| VARIABLES | mean | sd | mean | sd | mean | sd |
| **Damage** | | | | | | |
| Relative Business Damage | 0 | 0 | 0.289 | 1.119 | 0.384 | 1.560 |
| Relative Residential Damage | 0 | 0 | 0.00423 | 0.0162 | 0.00436 | 0.0191 |
| **BalanceSheet** | | | | | | |
| Total Assets | 333,273 | 428,414 | 160,492 | 77,858 | 768,524 | 624,525 |
| Growth Rate Total Assets | 2.458 | 5.693 | 2.584 | 5.732 | 1.713 | 4.130 |
| Deposit Share of Total Assets | 83.86 | 6.144 | 84.33 | 5.867 | 82.45 | 6.469 |
| Loan Share of Total Assets | 69.09 | 9.943 | 70.01 | 10.42 | 68.82 | 9.779 |
| Business Loans Share | 56.40 | 18.42 | 55.79 | 19.19 | 58.33 | 17.33 |
| Growth Total Loans | 2.635 | 5.563 | 2.691 | 5.803 | 1.976 | 3.977 |
| Growth Real Estate Loans | 2.987 | 7.387 | 3.030 | 6.465 | 2.073 | 4.783 |
| Growth Commercial and Industrial Loans | 1.737 | 16.41 | 2.381 | 14.39 | 2.014 | 13.62 |
| Growth Non-residential RE Loans | 2.832 | 15.52 | 2.362 | 10.68 | 2.640 | 6.986 |
| Growth Consumer Loans | -0.595 | 19.28 | 0.688 | 29.99 | 0.188 | 13.33 |
| **LoanQuality** | | | | | | |
| Allowance for Loan Loss over Loans | 1.428 | 0.652 | 1.408 | 0.665 | 1.459 | 0.652 |
| Share Non-performing Loans (out of Gross Loans) | 1.482 | 1.870 | 1.274 | 1.595 | 1.875 | 2.077 |
| Growth Allowance for Loan Loss | 2.301 | 9.514 | 2.783 | 10.53 | 1.729 | 10.05 |
| **Performance** | | | | | | |
| Growth Net Interest Income | 2.280 | 6.794 | 3.453 | 7.523 | 1.904 | 4.734 |
| Net Income Before Extra over Total Loans (Quarterly) | 0.417 | 0.392 | 0.446 | 0.445 | 0.380 | 0.390 |
| Total Capital Ratio | 14.75 | 4.189 | 15.01 | 4.518 | 14.37 | 3.264 |
| N | 1,695 | | 562 | | 252 | |

Table 4: Access to Local Finance and Industry Employment

This table provides estimates from $\text{EmpGrowth}_{c,i,t} = \beta\text{HurricaneLoss}_{c,t} + \psi\text{HurricaneLoss}_{c,t} \times \text{LocalFinance}_{c,t} + \gamma\text{LocalFinance}_{c,t} + \kappa Z_{c,i,t} + \alpha_{c,i} + \gamma_{i,s,t} + \epsilon_{c,i,t}$. The outcome variable in each case is monthly employment growth of an industry in a county. Hurricanes are based on major disaster declarations by FEMA between 1999 and 2019. I exclude Natural Resources and Mining, Construction, Financial Activities, Information, and Education and Healthcare, as well as industry-county observations if median total employment is below 100. Loss is relative business damage in a county, during a hurricane impact month or up to two months after the. Finance is the fraction of county deposits held in local banks twelve months before the current month. The last three columns use alternative measures of access to local finance: log of deposits held in local banks, fraction of local banks, log of total local banks. Residential Loss is relative residential damage in a county during the impact month or up to two month after. Po Displacements is the relative FEMA grants specifically used for rental payments for displaced households during the impact month or up to two month after. GDP is the 12 month lag of industry output in a county. Labor Productivity is the 12 month lag of industry average weekly earnings in a county. 20-less Employee Firms/3-less Year Old Firms is the faction of total industry workers employed by establishments with less than 20 employees/in existence for less than three years in a county. GDP HHI is calculated based on GDP shares by industry in a county. Group 4/Group 10 is the quartile/decile of the county-industry within the state, based on lagged GDP. The bottom three rows provide an estimate of the effect of Damage Business at the 25th, 50th, and 75th percentile of Local Finance. Column (6)/(7) restricts the sample to hurricanes causing more/less than \$1 bil. in a state. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Dep Variable: Monthly Employment Growth** | | | | | | | | | |
| | *Local Finance Measure*: | | | | | | | *Alternative Local Finance Measures* | | |
| | Fraction Local Bank Deposits | | | | | | | Log Loc Dep | Fr Loc Banks | Log Loc Banks |
| Loss | -0.240*** | -0.233*** | -0.222*** | -0.214*** | -0.245*** | -0.225*** | -1.141*** | -0.270*** | -0.193*** | -0.156** |
| | (0.0476) | (0.0468) | (0.0431) | (0.0473) | (0.0496) | (0.0467) | (0.387) | (0.0720) | (0.0508) | (0.0605) |
| Loss x Finance | 0.636*** | 0.643*** | 0.608*** | 0.582*** | 0.686*** | 0.523** | 3.447** | 0.0208*** | 0.681** | 0.0993 |
| | (0.220) | (0.218) | (0.195) | (0.206) | (0.241) | (0.251) | (1.490) | (0.00641) | (0.306) | (0.0661) |
| Finance | -0.000773 | -0.00533*** | -0.00258 | -0.00332* | -0.00316 | -0.00342 | -0.00216 | -0.000159** | -0.00559** | -0.00161* |
| | (0.00178) | (0.00200) | (0.00217) | (0.00196) | (0.00195) | (0.00332) | (0.00354) | (7.71e-05) | (0.00277) | (0.000849) |
| Residential Loss | -0.0755* | -0.0752* | -0.0621* | -0.0553 | -0.0702* | -0.0136 | -0.524 | -0.0701* | -0.0782* | -0.0804* |
| | (0.0435) | (0.0441) | (0.0371) | (0.0373) | (0.0374) | (0.0328) | (0.541) | (0.0384) | (0.0410) | (0.0442) |
| Pop Displacements | -0.199 | -0.240 | -0.313 | -0.329 | -0.286 | -0.584*** | 33.14** | -0.336 | -0.285 | -0.248 |
| | (0.217) | (0.215) | (0.193) | (0.205) | (0.204) | (0.175) | (16.03) | (0.223) | (0.202) | (0.217) |
| GDP | | 0.00161 | -0.000747 | -0.00163 | -0.00130 | -0.00109 | -0.000951 | -0.00145 | -0.00143 | -0.00148 |
| | | (0.00104) | (0.000848) | (0.00107) | (0.00172) | (0.00292) | (0.00344) | (0.00176) | (0.00173) | (0.00171) |
| Labor Productivity | | -0.00842*** | -0.00757** | -0.00621** | -0.00362 | 0.00204 | -0.00798 | -0.00354 | -0.00367 | -0.00357 |
| | | (0.00218) | (0.00299) | (0.00282) | (0.00424) | (0.00692) | (0.00494) | (0.00427) | (0.00424) | (0.00424) |
| 20-less Employee Firms | | 0.00757* | 0.00733* | 0.00993** | 0.0144*** | -0.000401 | 0.0186* | 0.0141** | 0.0146*** | 0.0144*** |
| | | (0.00417) | (0.00404) | (0.00430) | (0.00535) | (0.00769) | (0.0105) | (0.00538) | (0.00543) | (0.00543) |
| 3-less Year Old Firms | | -0.00240 | -0.000947 | -0.00393 | -0.000843 | -0.0100 | -0.000395 | -0.000825 | -0.000794 | -0.000971 |
| | | (0.00340) | (0.00294) | (0.00337) | (0.00396) | (0.0107) | (0.00767) | (0.00399) | (0.00400) | (0.00402) |
| GDP HHI | | 0.00907* | 0.000555 | -0.00169 | 0.00153 | -0.00110 | 0.00385 | 0.00191 | 0.00191 | 0.00208 |
| | | (0.00497) | (0.00416) | (0.00403) | (0.00694) | (0.0121) | (0.0102) | (0.00676) | (0.00687) | (0.00673) |
| Observations | 70,127 | 65,970 | 65,910 | 64,274 | 59,483 | 25,901 | 33,214 | 59,483 | 59,483 | 59,483 |
| R-squared | 0.056 | 0.057 | 0.185 | 0.281 | 0.355 | 0.471 | 0.408 | 0.354 | 0.354 | 0.354 |
| County x Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State x Sector x Month FE | | | Yes | | | | | | | |
| Group 4 x Sector x Month FE | | | | Yes | | | | | | |
| Group 10 x Sector x Month FE | | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| All Hurricanes | Yes | Yes | Yes | Yes | Yes | Over \$1b | Less \$1b | Yes | Yes | Yes |
| Loss: Finance p25 | -0.240*** | -0.233*** | -0.222*** | -0.214*** | -0.245*** | -0.225*** | -1.141*** | -0.270*** | -0.193*** | -0.156** |
| | (0.0476) | (0.0468) | (0.0431) | (0.0473) | (0.0496) | (0.0467) | (0.387) | (0.0720) | (0.0508) | (0.0605) |
| Loss: Finance p50 | -0.151*** | -0.143*** | -0.136*** | -0.132*** | -0.149*** | -0.151*** | -0.659** | -0.0282 | -0.0910* | -0.0870 |
| | (0.0378) | (0.0379) | (0.0358) | (0.0397) | (0.0424) | (0.0403) | (0.325) | (0.0564) | (0.0531) | (0.0545) |
| Loss: Finance p75 | -0.0109 | -0.00166 | -0.00264 | -0.00441 | 0.00182 | -0.0362 | 0.0998 | -0.00595 | -0.00251 | -0.0473 |
| | (0.0629) | (0.0634) | (0.0583) | (0.0623) | (0.0731) | (0.0758) | (0.462) | (0.0596) | (0.0801) | (0.0669) |

## Table 5: Local Finance and Employment by Individual Industries

This table provides estimates from $\text{EmpGrowth}_{c,i,t} = \beta\text{HurricaneLoss}_{c,t} + \psi\text{HurricaneLoss}_{c,t} \times \text{LocalFinance}_{c,t} + \gamma\text{LocalFinance}_{c,t} + \kappa Z_{c,i,t} + \alpha_{c,i} + \gamma_{i,s,t} + \epsilon_{c,i,t}$ using a different set of outcome variables compared to Table 4. Estab refers to the quarterly growth rate of the number of establishments (from BLS) in a county-industry. Small firms refers to the quarterly employment growth rate at firms with less than 20 employees (from QWI) in a county-industry. Columns (3) through (7) limit the sample from Table 4 to a specific industry sector. For a definition of variables and the baseline sample, please refer to Table 4. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Estab | Small Firms | Manufact | Trade/Trans/Util | Prof. Services | Hospitality | Other Serv. |
| Loss | -0.0409 | -0.950*** | -0.0965 | -0.221*** | -0.189** | -0.453*** | -0.283** |
| | (0.0487) | (0.321) | (0.0769) | (0.0517) | (0.0835) | (0.143) | (0.120) |
| Loss x Finance | 0.273** | 2.110** | 0.217 | 0.365** | 1.326*** | 0.849* | 0.729* |
| | (0.106) | (1.019) | (0.265) | (0.129) | (0.320) | (0.416) | (0.352) |
| Finance | 0.000409 | -0.00505 | -0.00791 | -5.52e-05 | -0.00498 | -0.000176 | -0.00508 |
| | (0.00303) | (0.0103) | (0.00554) | (0.00347) | (0.00455) | (0.00334) | (0.00621) |
| Residential Loss | -0.0516* | -0.328** | -0.0571 | 0.0309 | -0.0870 | -0.199** | -0.0156 |
| | (0.0274) | (0.162) | (0.0631) | (0.0518) | (0.0648) | (0.0779) | (0.0716) |
| Pop Displacements | -0.315* | -0.359 | -0.466*** | -0.464** | -0.346 | 0.184 | -0.346 |
| | (0.177) | (0.675) | (0.153) | (0.175) | (0.466) | (0.578) | (0.319) |
| GDP | -0.00345 | -0.00758 | 0.00283 | -2.47e-05 | -0.00318 | -0.00577 | -0.00618 |
| | (0.00264) | (0.0143) | (0.00334) | (0.00255) | (0.00380) | (0.00520) | (0.00859) |
| Labor Productivity | 0.00717** | -0.00563 | -0.0101 | -0.00786 | -0.00961* | 0.0147 | 0.00578 |
| | (0.00299) | (0.0207) | (0.00885) | (0.00645) | (0.00469) | (0.0132) | (0.0137) |
| 20-less Employee Firms | 0.00347 | -0.0181 | 0.0174 | 0.00338 | 0.0244** | 0.00429 | 0.00563 |
| | (0.00750) | (0.0206) | (0.0212) | (0.00577) | (0.0101) | (0.00789) | (0.00938) |
| 3-less Year Old Firms | -0.00192 | -0.0189 | -0.00294 | 0.00354 | -0.00194 | -0.0148** | 0.0174* |
| | (0.00618) | (0.0198) | (0.0115) | (0.0134) | (0.00459) | (0.00695) | (0.00948) |
| GDP HHI | 0.00421 | -0.0222 | 0.0365 | -0.000337 | -0.0136 | 0.00471 | -0.00169 |
| | (0.00755) | (0.0310) | (0.0233) | (0.00497) | (0.0166) | (0.0104) | (0.00913) |
| Observations | 19,658 | 17,529 | 12,209 | 13,384 | 11,332 | 12,542 | 10,016 |
| R-squared | 0.464 | 0.540 | 0.325 | 0.345 | 0.323 | 0.426 | 0.301 |
| County x Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Group 10 x Sector x Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| All Hurricanes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loss: Finance p25 | -0.0409 | -0.950*** | -0.0965 | -0.221*** | -0.189** | -0.453*** | -0.283** |
| | (0.0487) | (0.321) | (0.0769) | (0.0517) | (0.0835) | (0.143) | (0.120) |
| Loss: Finance p50 | -0.00274 | -0.655** | -0.0661 | -0.170*** | -0.00310 | -0.334*** | -0.181 |
| | (0.0431) | (0.265) | (0.0600) | (0.0473) | (0.0827) | (0.108) | (0.127) |
| Loss: Finance p75 | 0.0573 | -0.190 | -0.0183 | -0.0899* | 0.289** | -0.147 | -0.0205 |
| | (0.0441) | (0.318) | (0.0742) | (0.0535) | (0.121) | (0.107) | (0.169) |

## Table 6: Local Finance, Employment Recovery, and Local County Characteristics

The estimates are based on the specification: $\text{EmpGrowth}_{c,i,t} = \beta\text{HurricaneLoss}_{c,t} + \psi\text{HurricaneLoss}_{c,t} \times \text{LocalFinance}_{c,t} + \eta\text{HurricaneLoss}_{c,t} \times \text{LocalFinance}_{c,t} \times \text{X}_{c,t} + \gamma\text{LocalFinance}_{c,t} + \gamma_2\text{X}_{c,t} + \psi_2\text{HurricaneLoss}_{c,t} \times \text{X}_{c,t} + \gamma_3\text{LocalFinance}_{c,t} \times \text{X}_{c,t} + \kappa Z_{c,i,t} + \alpha_{c,i} + \gamma_{i,t} + \epsilon_{c,i,t}$. Productivity is an indicator for all counties with above median (state) lagged earnings in an industry. Industry Concentration is an indicator for counties with above median GDP HHI index, based on GDP shares of all industry super-sectors in a county. Geographic Concentration is an indicator for counties with total employment share in the top census tract above three times the share if employment is equally distributed across all tracts. For a definition of the rest of the variables and the baseline sample, please refer to Table 4. Included in the estimation but omitted from the table are the set of controls in Table 4 and the remaining interactions of the indicator variables with Local Finance. The bottom panel presents the marginal effect of business damages on employment growth for various levels of LocalFinance, separated for counties with different productivity/industry concentration/geographic concentration. In the last column, X=0 refers to counties with lower productivity, lower industrial/geographic concentration; X=1 refers to high productivity, lower industrial/geographic concentration. *** p<0.01, ** p<0.05, * p<0.1.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | Dep Variable: Monthly Employment Growth | | | | |
| Loss | -0.245*** | -0.136*** | -0.289*** | -0.322*** | -0.268*** |
| | (0.0496) | (0.0445) | (0.0644) | (0.0763) | (0.0809) |
| Loss x Finance | 0.686*** | 0.208 | 1.021*** | 0.789*** | 0.760*** |
| | (0.241) | (0.125) | (0.238) | (0.266) | (0.166) |
| Loss x Finance x Productivity | | 0.862** | | | 0.839** |
| | | (0.415) | | | (0.410) |
| Loss x Finance x Industry Concentration | | | -0.466** | | -0.539** |
| | | | (0.210) | | (0.205) |
| Loss x Finance x Geographic Concentration | | | | -0.496** | -0.472** |
| | | | | (0.226) | (0.196) |
| Loss x Productivity | | -0.251** | | | -0.219* |
| | | (0.118) | | | (0.114) |
| Loss x Industry Concentration | | | 0.0164 | | 0.00888 |
| | | | (0.0677) | | (0.0627) |
| Loss x Geographic Concentration | | | | 0.153* | 0.165** |
| | | | | (0.0913) | (0.0817) |
| Observations | 59,483 | 59,418 | 59,418 | 57,042 | 57,042 |
| R-squared | 0.355 | 0.354 | 0.353 | 0.349 | 0.349 |
| County x Ind FE | Yes | Yes | Yes | Yes | Yes |
| CountyGr10 x Ind x YearMonth FE | Yes | Yes | Yes | Yes | Yes |
| All Hurricanes | Yes | Yes | Yes | Yes | Yes |
| X= Productivity/Industry Concentration/Geographic Concentration | | | | | |
| Loss: Finance p25 and X=0 | -0.240*** | -0.136*** | -0.289*** | -0.322*** | -0.268*** |
| | (0.0476) | (0.0445) | (0.0644) | (0.0763) | (0.0809) |
| Loss: Finance p50 and X=0 | -0.151*** | -0.107*** | -0.146*** | -0.212*** | -0.162** |
| | (0.0378) | (0.0410) | (0.0499) | (0.0623) | (0.0651) |
| Loss: Finance p75 and X=0 | -0.0109 | -0.0613 | 0.0786 | -0.0381 | 0.00544 |
| | (0.0629) | (0.0497) | (0.0661) | (0.0802) | (0.0528) |
| Loss: Finance p25 and X=1 | | -0.387*** | -0.273*** | -0.169*** | -0.487*** |
| | | (0.100) | (0.0554) | (0.0516) | (0.110) |
| Loss: Finance p50 and X=1 | | -0.237*** | -0.195*** | -0.128*** | -0.263*** |
| | | (0.0699) | (0.0461) | (0.0434) | (0.0769) |
| Loss: Finance p75 and X=1 | | -0.00182 | -0.0726 | -0.0639 | 0.0891 |
| | | (0.0932) | (0.0805) | (0.0783) | (0.0938) |

## Table 7: Bank Lending and Hurricane Exposure

This table examines the difference in the impact of business losses on the performance of banks of varying size. For discussion of the sample selection, please refer to Table 3. It is based on the specification: $Y_{b,c,q} = \beta \text{HurricaneLoss}_{c,q} \times \text{Small}_{b,(q-4)} + \gamma W_{b,q-4} + \alpha_b + \lambda_{c,q} + \epsilon_{b,c,q}$. Small/Big Banks are local lenders with more than 65% of deposits in one county and lagged assets below/above \$300M. Columns (1)-(7) are based on specification (3) with county-quarter fixed effects, which allow for the estimation of the effect of business damage on small community banks relative to big ones. Columns (8)-(14) use county-group4-quarter fixed effects and allow for the estimation of the effect of damage for both bank types. County-group4 is defined as the total county GDP quartile within a state. LoanLossAllowRatio is Loan-loss-allowance over gross loans; GrNetIntIcnome is the quarterly growth of Net Interest Income; NetInc/Loans is Net Income Before Extra Items over total gross loans; Tier2CapRatio is the Tier2 risk-based capital ratio; GrTotLoans is the quarterly growth rate of total loans; GrCILoans is the quarterly growth rate of commercial and industrial loans; GrIndivLoans is the quarterly growth rate of loans to individuals. Each of the bank controls are four-quarter lags. *** p<0.01, ** p<0.05, * p<0.1.

| VARIABLES | (1) LoanLoss AllowRatio | (2) GrNet IntIncome | (3) NetInc /Loans | (4) Tier2 CapRatio | (5) GrTot Loans | (6) GrCI Loans | (7) GrIndiv Loanst | (8) LoanLoss AllowRatio | (9) GrNet IntIncome | (10) NetInc /Loans | (11) Tier2 CapRatio | (12) GrTot Loans | (13) GrCI Loans | (14) GrIndiv Loans |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loss x Small Bank | -4.052** | 0.505*** | 0.0683*** | 8.145*** | 0.286** | 0.993*** | 3.606** | 0.822** | -0.460* | -0.00310 | -2.501*** | 0.218* | 1.486** | 0.823 |
| | (1.926) | (0.115) | (0.0211) | (1.011) | (0.117) | (0.297) | (1.767) | (0.325) | (0.265) | (0.00397) | (0.877) | (0.121) | (0.654) | (0.900) |
| Loss x Big Bank | | | | | | | | 4.904** | -1.079*** | -0.0713*** | -10.43*** | -0.0258 | 0.659** | -2.623** |
| | | | | | | | | (2.156) | (0.294) | (0.0247) | (1.209) | (0.0873) | (0.313) | (1.068) |
| Log Assets | -0.311 | -0.120 | -0.000716 | -0.731 | -0.0386 | 0.0613 | -0.0259 | -0.217 | 0.00782 | -0.000922 | -1.588 | -0.0948 | 0.108 | -0.164 |
| | (0.289) | (0.141) | (0.00577) | (1.504) | (0.126) | (0.384) | (0.672) | (0.226) | (0.125) | (0.00535) | (1.163) | (0.0928) | (0.405) | (0.508) |
| Log Deposits | 0.367 | 0.0957 | -0.00617 | 0.701 | -0.0299 | -0.0691 | -0.0949 | 0.286 | 0.00665 | -0.00551 | 1.086 | 0.0236 | -0.135 | 0.113 |
| | (0.258) | (0.123) | (0.00412) | (1.327) | (0.110) | (0.327) | (0.662) | (0.214) | (0.103) | (0.00393) | (1.132) | (0.0991) | (0.352) | (0.466) |
| Log Unused Loan Commit | -0.0330* | -0.00736 | -0.000805* | 0.272 | -0.000454 | -0.0262 | -0.0469 | -0.0270 | -0.0190** | -0.000562 | 0.257 | -0.00568 | -0.0266 | -0.0306 |
| | (0.0184) | (0.00840) | (0.000482) | (0.164) | (0.00777) | (0.0274) | (0.0525) | (0.0193) | (0.00917) | (0.000515) | (0.167) | (0.00728) | (0.0239) | (0.0434) |
| Captial Ratio | 0.000960 | -0.00319 | 5.28e-05 | -0.0933 | -0.00367* | -0.00625 | -0.00531 | -0.000735 | -0.00419 | 4.58e-05 | -0.0798 | -0.00344 | -0.00425 | -0.00312 |
| | (0.00500) | (0.00348) | (0.000106) | (0.0596) | (0.00213) | (0.00557) | (0.00867) | (0.00483) | (0.00296) | (8.84e-05) | (0.0568) | (0.00230) | (0.00557) | (0.00615) |
| Share Non-performing | 1.812** | 0.669* | 0.0115 | 6.972 | 0.0950 | 1.651* | 0.385 | 1.705** | 0.521 | 0.00895 | 2.692 | -0.0364 | 1.151 | 0.143 |
| | (0.731) | (0.382) | (0.0318) | (7.063) | (0.178) | (0.946) | (1.135) | (0.685) | (0.384) | (0.0358) | (5.233) | (0.158) | (0.939) | (1.178) |
| Share Business Loans | 0.238 | -0.194** | -0.00538* | 1.002 | -0.0226 | 0.258 | 0.241 | 0.325 | -0.234*** | -0.00709* | 0.281 | -0.0824 | 0.0517 | 0.0850 |
| | (0.195) | (0.0782) | (0.00299) | (1.028) | (0.115) | (0.220) | (0.285) | (0.225) | (0.0736) | (0.00394) | (1.512) | (0.0963) | (0.238) | (0.282) |
| Net income over Loans | 1.533 | 1.794 | 0.0282 | 20.53 | -0.134 | 0.307 | -1.956 | 2.431 | 2.525** | 0.00944 | 11.99 | 0.0862 | 1.660 | -2.546 |
| | (2.689) | (1.221) | (0.0373) | (40.95) | (0.386) | (1.349) | (3.765) | (2.881) | (1.034) | (0.0358) | (44.69) | (0.473) | (1.584) | (3.539) |
| Observations | 2,509 | 2,499 | 2,509 | 2,509 | 2,509 | 2,507 | 2,485 | 2,494 | 2,484 | 2,494 | 2,494 | 2,494 | 2,492 | 2,470 |
| R-squared | 0.986 | 0.683 | 0.852 | 0.982 | 0.701 | 0.600 | 0.535 | 0.982 | 0.555 | 0.810 | 0.975 | 0.632 | 0.506 | 0.412 |
| Bank x Hurricane FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | | | | | | | |
| Group 4 x Quarter FE | | | | | | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 8: Varying Share of Local Deposits

This table examines the stability of the main effect Local Finance with respect to the definition of local lenders. All of the results are based on specification (1). Columns (1)-(3) use total count-industry monthly employment growth as a dependent variable; columns (4)-(6) use quarterly employment growth at firms with less than 20 employees; columns (7)-(9) use monthly employment growth only in the Trade/Transportation/Utilities sector. The columns labeled 66% Dep use a measure of local finance (fraction of local deposits) where local lenders have more than 65% of deposits in one county. Columns labeled 90% Dep/100% Dep assume that local lenders have more than 90%/all deposits in one county. For definitions of variables and selection of sample please refer to Table 4 and Table 5.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Employment Growth: All | | | Employment Growth: Small Firms | | | Employment Growth: Trade Sector | | |
| VARIABLES | 66% Dep | 90% Dep | 100% Dep | 66% Dep | 90% Dep | 100% Dep | 66% Dep | 90% Dep | 100% Dep |
| Loss | -0.245*** | -0.166*** | -0.146*** | -0.950*** | -0.798*** | -0.690** | -0.221*** | -0.188*** | -0.177*** |
| | (0.0496) | (0.0475) | (0.0459) | (0.321) | (0.298) | (0.271) | (0.0517) | (0.0518) | (0.0496) |
| Loss x Finance | 0.686*** | 0.490** | 0.437** | 2.110** | 1.902* | 1.617 | 0.365** | 0.321** | 0.270** |
| | (0.241) | (0.196) | (0.208) | (1.019) | (1.050) | (1.078) | (0.129) | (0.121) | (0.111) |
| Finance | -0.00316 | -0.00272 | 0.000272 | -0.00505 | -0.0171 | -0.0205* | -5.52e-05 | -0.000674 | 0.000630 |
| | (0.00195) | (0.00215) | (0.00268) | (0.0103) | (0.0104) | (0.0113) | (0.00347) | (0.00259) | (0.00325) |
| Residential Loss | -0.0702* | -0.0800* | -0.0811* | -0.328** | -0.324** | -0.329** | 0.0309 | 0.0236 | 0.0239 |
| | (0.0374) | (0.0421) | (0.0429) | (0.162) | (0.162) | (0.164) | (0.0518) | (0.0524) | (0.0523) |
| Pop Displacements | -0.286 | -0.182 | -0.106 | -0.359 | -0.124 | 0.113 | -0.464** | -0.395* | -0.349* |
| | (0.204) | (0.241) | (0.253) | (0.675) | (0.728) | (0.788) | (0.175) | (0.204) | (0.183) |
| GDP | -0.00130 | -0.00124 | -0.00137 | -0.00758 | -0.00672 | -0.00696 | -2.47e-05 | 4.21e-05 | -3.63e-05 |
| | (0.00172) | (0.00166) | (0.00166) | (0.0143) | (0.0141) | (0.0142) | (0.00255) | (0.00249) | (0.00251) |
| Labor Productivity | -0.00362 | -0.00353 | -0.00365 | -0.00563 | -0.00513 | -0.00509 | -0.00786 | -0.00771 | -0.00795 |
| | (0.00424) | (0.00422) | (0.00421) | (0.0207) | (0.0208) | (0.0208) | (0.00645) | (0.00634) | (0.00633) |
| 20-less Employee Firms | 0.0144*** | 0.0144** | 0.0144** | -0.0181 | -0.0172 | -0.0172 | 0.00338 | 0.00371 | 0.00372 |
| | (0.00535) | (0.00552) | (0.00550) | (0.0206) | (0.0208) | (0.0206) | (0.00577) | (0.00585) | (0.00589) |
| 3-less Year Old Firms | -0.000843 | -0.00137 | -0.00116 | -0.0189 | -0.0205 | -0.0188 | 0.00354 | 0.00313 | 0.00277 |
| | (0.00396) | (0.00400) | (0.00403) | (0.0198) | (0.0197) | (0.0196) | (0.0134) | (0.0137) | (0.0137) |
| GDP HHI | 0.00153 | 0.00203 | 0.00221 | -0.0222 | -0.0195 | -0.0186 | -0.000337 | 2.24e-05 | 0.000159 |
| | (0.00694) | (0.00682) | (0.00677) | (0.0310) | (0.0309) | (0.0312) | (0.00497) | (0.00520) | (0.00511) |
| Observations | 59,483 | 59,483 | 59,483 | 17,529 | 17,529 | 17,529 | 13,384 | 13,384 | 13,384 |
| R-squared | 0.355 | 0.354 | 0.354 | 0.540 | 0.539 | 0.539 | 0.345 | 0.345 | 0.344 |
| County x Sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Group 10 x Sector x Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loss: Finance p25 | -0.245*** | -0.166*** | -0.146*** | -0.950*** | -0.798*** | -0.690** | -0.221*** | -0.188*** | -0.177*** |
| | (0.0496) | (0.0475) | (0.0459) | (0.321) | (0.298) | (0.271) | (0.0517) | (0.0518) | (0.0496) |
| Loss: Finance p50 | -0.149*** | -0.0974* | -0.0853 | -0.655** | -0.532** | -0.463* | -0.170*** | -0.143*** | -0.139*** |
| | (0.0424) | (0.0520) | (0.0559) | (0.265) | (0.263) | (0.268) | (0.0473) | (0.0463) | (0.0458) |
| Loss: Finance p75 | 0.00182 | 0.0103 | 0.0108 | -0.190 | -0.114 | -0.107 | -0.0899* | -0.0720 | -0.0794 |
| | (0.0731) | (0.0802) | (0.0903) | (0.318) | (0.356) | (0.402) | (0.0535) | (0.0498) | (0.0500) |

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Employment Impact of Business Damage

This figure plots average employment growth for counties with business damage above/below 0.5% for each of the five months before and after the impact. The dynamic response for places with above 0.5% business loss is provided in the top panel. The grey lines represent the 95% confidence interval. Month 0 is the month of the impact of a hurricane.

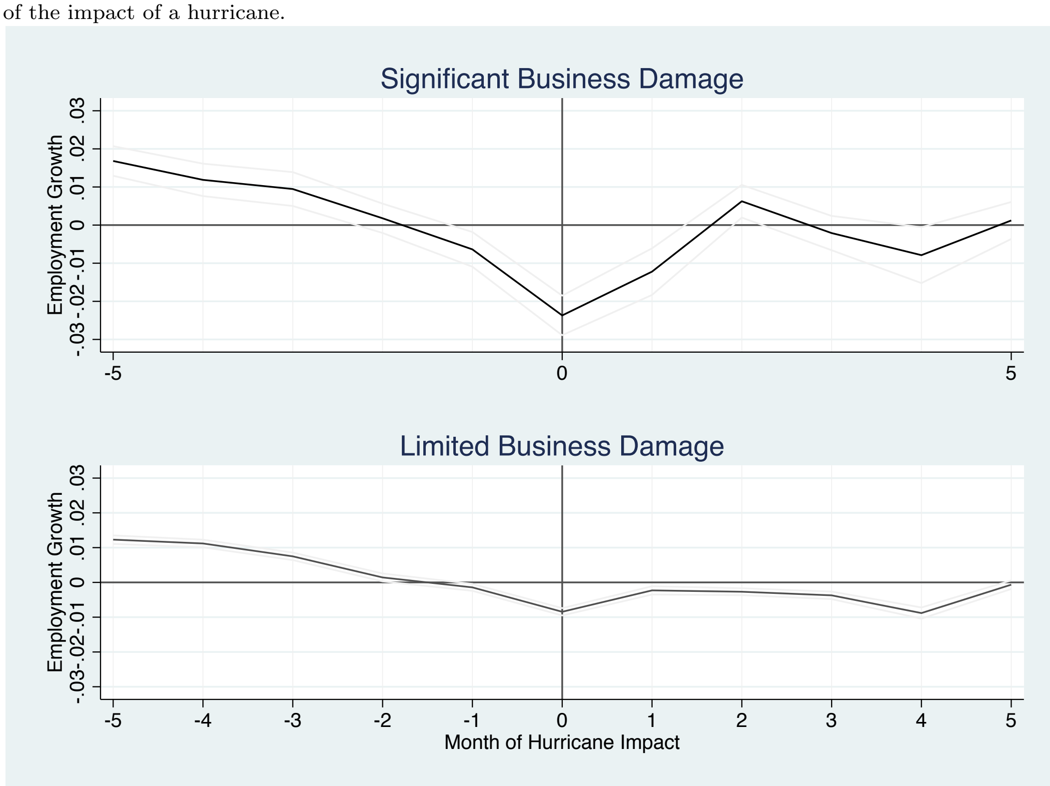
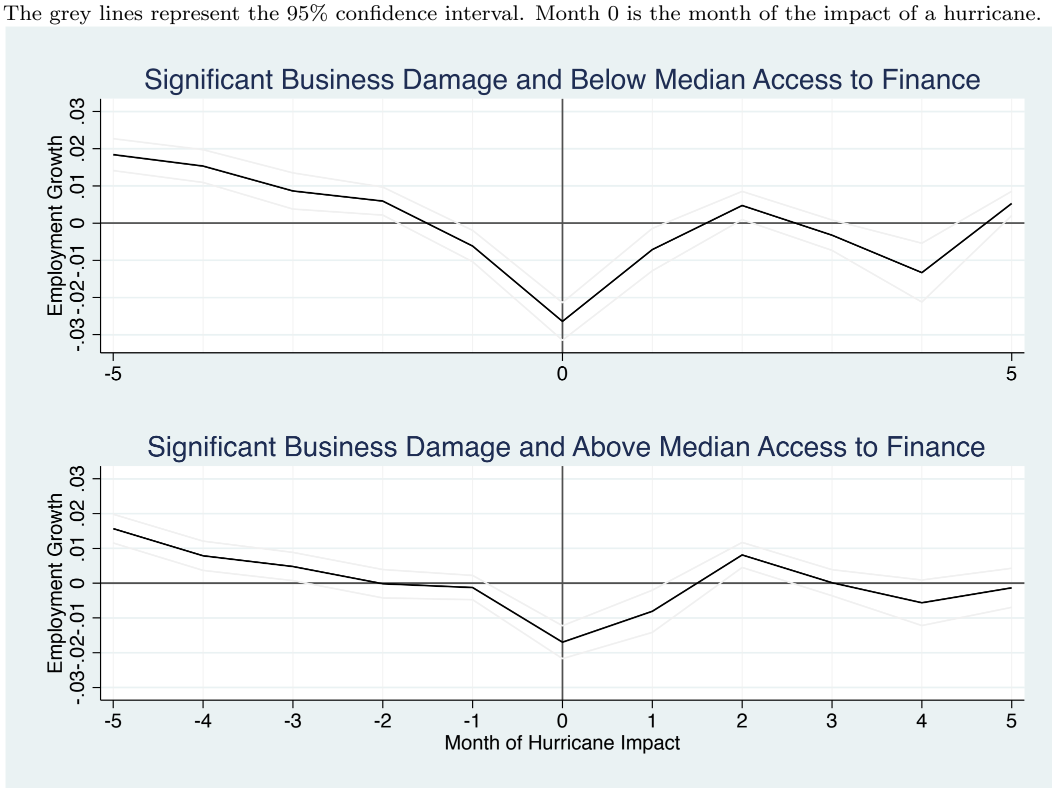


Figure 2: Access to Local Finance and Business Damage

This figure plots average employment growth for counties with business damage above 0.5%, divided by the median access to local finance. Access to Finance is measured by the fraction of local deposits in a county. The grey lines represent the 95% confidence interval. Month 0 is the month of the impact of a hurricane.



# Appendix (for online publication)

## Appendix A: Robustness and Extensions

### Table A1: Business Damage by State

This table lists summary statistics for relative business damage by individual states. Excluded are states with less than 10 county observations. Relative damage is in percentages.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | N | mean | p75 | p90 | sd |
| AL | 147 | 0.224 | 0.109 | 0.371 | 0.855 |
| AR | 17 | 0.103 | 0.174 | 0.280 | 0.0961 |
| CT | 18 | 0.0442 | 0.0714 | 0.100 | 0.0412 |
| FL | 349 | 1.255 | 0.618 | 1.817 | 5.081 |
| GA | 322 | 0.283 | 0.118 | 0.428 | 1.359 |
| LA | 335 | 0.695 | 0.195 | 0.637 | 4.037 |
| MA | 15 | 0.0779 | 0.0296 | 0.242 | 0.184 |
| MD | 78 | 0.108 | 0.0910 | 0.320 | 0.268 |
| MS | 198 | 1.143 | 0.206 | 1.347 | 5.196 |
| NC | 333 | 0.553 | 0.333 | 1.340 | 1.590 |
| NH | 16 | 0.0578 | 0.0554 | 0.196 | 0.107 |
| NJ | 56 | 0.281 | 0.141 | 0.543 | 0.739 |
| NY | 73 | 0.839 | 0.348 | 2.070 | 2.657 |
| PA | 134 | 0.145 | 0.126 | 0.273 | 0.364 |
| SC | 130 | 0.215 | 0.116 | 0.399 | 0.842 |
| TX | 242 | 1.293 | 0.406 | 1.986 | 7.236 |
| VA | 130 | 0.110 | 0.0623 | 0.243 | 0.349 |
| VT | 13 | 1.047 | 1.065 | 3.085 | 1.333 |
| WV | 25 | 0.0238 | 0.0330 | 0.0595 | 0.0311 |

### Table A2: Disaster Loans to Businesses by Industry Classification

This table lists summary statistics at the county level for states with hurricanes. Hurricanes are based on major disaster declarations by FEMA between 1999 and 2019 (33 in total). Business loss consists of SBA's business loans, FEMA's public assistance grants, and flood insurance payments related to non-residential buildings. Residential loss consists of SBA's homeowners loss, FEMA's IHP loss, and flood insurance payments related to residential buildings. Counties are divided into groups based on business loss and access to local finance. The group with no (positive) business damage, Bus Damage=0 (Bus Damage>0), lists monthly average and standard deviation during the impact month for counties with no (positive) business impact. The last four columns divide the counties with a positive business damage based on the median of the fraction of local deposits in the county. Disaster loan shares are based on a loan-level information with 6-digit NAICS information for 13 hurricanes between 2002 and 2012. Data is listed as percentages but is utilized in non-percentage form in the rest of the paper.

| | Bus Damage=0 | | Bus Damage>0 | | Bus Damage>0 LocDep<Median | | Bus Damage>0 LocDep>Median | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | mean | sd | mean | sd | mean | sd | mean | sd |
| **HurricaneDamage** | | | | | | | | |
| Share Disaster Loans Natural Resources and Mining in % | 0 | 0 | 5.700 | 15.46 | 3.945 | 12.16 | 7.014 | 17.45 |
| Share Disaster Loans Construction in % | 0 | 0 | 3.305 | 9.257 | 3.286 | 9.835 | 3.318 | 8.821 |
| Share Disaster Loans Manufacturing in % | 0 | 0 | 1.809 | 4.698 | 1.707 | 4.729 | 1.886 | 4.683 |
| Share Disaster Loans Trade-Transportation-Utilities in % | 0 | 0 | 16.59 | 22.82 | 12.88 | 17.51 | 19.37 | 25.78 |
| Share Disaster Loans Information in % | 0 | 0 | 0.660 | 5.838 | 0.968 | 7.936 | 0.430 | 3.536 |
| Share Disaster Loans FIRE in % | 0 | 0 | 40.93 | 30.13 | 44.15 | 29.45 | 38.52 | 30.47 |
| Share Disaster Loans Professional and Business Services in % | 0 | 0 | 4.788 | 10.91 | 5.948 | 11.58 | 3.919 | 10.33 |
| Share Disaster Loans Education and Healthcare in % | 0 | 0 | 3.529 | 9.367 | 2.697 | 6.171 | 4.152 | 11.15 |
| Share Disaster Loans Leisure and Hospitality in % | 0 | 0 | 11.02 | 19.19 | 11.19 | 20.31 | 10.90 | 18.36 |
| Share Disaster Other Services in % | 0 | 0 | 11.67 | 19.79 | 13.24 | 21.81 | 10.49 | 18.09 |