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

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Abstract

This paper examines the role of local lenders during recoveries from 33 hurricanes between 1999 and 2019, using a novel dataset of residential and commercial losses. I estimate the average effect of local finance and identify necessary conditions allowing lenders to mitigate employment shocks. The evidence consistently shows that higher access to local finance dampens the county employment contractions at the average industry, at individual sectors (except manufacturing), at smaller businesses, and during block-buster/less-costly disasters. Community banks aid the recovery by both identifying firms with potential to survive and avoiding direct loan losses. To support the former, I show that local finance has a stronger effect in more productive counties. In support of the latter, I show that local finance has a stronger effect in more spatially/geographically dispersed counties, and that smaller community banks outperform/lend more than bigger ones within affected counties.

JEL Classification:

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

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1 Introduction

Hurricanes disrupt economic activity – counties with business damage contract total employment by 0.65% during the month of impact (unaffected ones grow by 0.13%). The effect is strongest for those employed by smaller businesses and can be permanent.[1] Direct damage to businesses reduces revenue either because it prevents them from functioning properly or drives away customer base.[2] Without revenue, owners have to rely on credit or personal savings to restore their business and bring back employees.[3] Many small enterprises lack the financial record or are engaged in lines of business which are hard to evaluate and rely on regional banks for credit.[4] Hurricanes present considerable challenges to community banks whose ability to recover from loan losses due to their geographic concentration and limited access to credit markets may compromise their ability to extend new loans.[5]

This paper examines the role of local lenders during the recovery phase following severe and widespread hurricanes, which can damage local businesses and limit banks' lending alike. I combine the wide scope of long-term studies with a detailed model of the short-term dynamic response, as in individual case studies, to highlight the role of community lenders and the main underpining factors.[6] I consider both whether small lenders, on average, mitigate negative employment shocks and also identify necessary conditions allowing them to assist in the recovery. The evidence consistently shows that increased access to local finance – measured by the fraction of deposits held by local banks, the log of local deposits, or the fraction of local banks – dampens the employment contraction resulting from business damages. This applies to the average industry in affected counties, to each sector on its own (except manufacturing), and has a particularly strong effect on small businesses. Community

[1] Based on averages from BLS county employment data for counties with Major Disaster Declarations between 1999 and 2019. Small businesses data is from QWI for establishments with less than 20 employees.

[2] See Kroll et al. (1991); Webb et al. (2000).

[3] See Basker and Miranda (2018).

[4] See Gilje (2019), Cortés and Strahan (2017), Berger et al. (2005).

[5] See Emmons et al. (2004), Aubuchon et al. (2010)

[6] For long-term studies see Strobl (2011), Deryugina (2017), Boustan et al. (2020); for case studies see Belasen and Polachek (2008), Guimaraes et al. (1993), Ewing et al. (2003), Meltzer et al. (2019).

banks aid in the recovery from blockbuster storms and less costly ones. A 1%-output-loss-event reduces employment growth by 0.25% at counties with low presence of local lenders, 0.15% at those with medium presence, and not at all at counties with high presence.

I consider a total of 33 hurricanes between 1999 and 2019 and develop a novel dataset, which distinguishes between residential and commercial losses. Damages during major disaster declarations are matched to a specific event, in a specific county, at a given date and include both insured and uninsured losses. I focus on a set of industries, which are most vulnerable, during a short period before and after the hurricane shock.[7] I classify banks as local if at least 65% of their deposits are located in a county and use the county fraction of local deposits as the main measure of access to local finance.[8]

The main empirical strategy is based on an event-study model of monthly employment growth by industry in each county, allowing for common county-industry shocks across a peer group. Key for identifying the effect of local finance is that business damage and local finance are not correlated with other factors related to the economic development in affected counties. Businesses install protective infrastructure or relocate from counties with regular hurricane incidence. Such adjustments can vary by the industry sector, the relative productivity of local firms, or the endowments of the local economy.[9] Local banks can also respond indirectly to anticipated future damages by co-relocating with business. I disentangle the link between business damage, local banking structure, and the underlying county differences by both directly controlling for county-industry characteristics and forming relative-output peer control groups. Both limit the effect of unobservable heterogeneity.[10] The key identifying assumption is that, exception for access to local finance, the county-industries in the peer group share the same underlying economic characteristics and are

[7] I identify industries which are likely to be directly affected using a limited dataset of SBA disaster loans which list the industry code for each borrower.

[8] This follows Meyer and Yeager (2001) and Cortés (2014).

[9] For example, the hospitality sector may find it appropriate to locate to places with higher exposure to weather shocks, while manufacturing will do the opposite.

[10] More specifically, I control for industry-specific output, labor productivity, proportion of small/young businesses, as well as residential damage, population displacement and industrial diversification.

likely to respond in a similar way to hurricane losses.

I test two distinct but complementary factors that can explain why community banks aid in recoveries. First, due to their proximity (Agarwal and Hauswald (2010); Degryse and Ongena (2005)) and specialization in servicing firms with limited financial track record (Berger et al. (2005)), community banks are uniquely positioned to identify businesses able to repay loans if they reopen (Basker and Miranda (2018)). To provide a test of this, I consider whether local finance has a higher impact in locations where businesses are more productive. In doing so, I explicitly allow such businesses to recover at different rates, regardless of local finance. The second factor is related to the ability of local banks to avoid direct losses to existing loans. Since community banks lend to a small number of clients they face lower market risk as opposed to idiosyncratic risk (due to borrower-specific defaults). As a result, business damage increases the variability in performance across local lenders but can leave the average unaffected. I consider the role of idiosyncratic risk in two different ways. First, I examine whether access to local finance has a lower effect in counties where activity is concentrated in the same industry or census tract (Gunther et al. (1999)). In such areas, losses are more strongly correlated across individual borrowers and more smaller lenders can face defaults, which limits additional lending. Second, I focus directly on the lending activity and loan performance after hurricanes. In the same county, I compare bigger banks, which diversify risk from individual defaults and have higher exposure to local market risk, to smaller ones, which face higher idiosyncratic risk (Yeager (2004)).

The results support the hypothesis that community banks help in the recovery by both being able to identify businesses with potential to survive and by avoiding direct loss to their existing portfolio of loans. The first factor explains why national banks may find it hard to step in during such disasters and the second explains why local banks are able to lend more.[11]

[11] I also find (evidence not presented) that local banks experience an increase in deposits, likely due to insurance claims and federal relief. This relieves the funding constraint but does not imply that they will actually lend more. Schüwer et al. (2019) shows that local banks increase security holdings.

I document that local banks mitigate contractions more in counties where the firms are more productive. Conversely, when local businesses are less likely to survive the hurricane loss, community banks will not extend credit and employment will contract. In high-productivity counties, access to local finance leads to stark differences in employment outcomes: a 1%-output-loss-event reduces employment by 0.4%/0.02% at counties with low/high access to finance. This finding is consistent with several existing studies showing that lenders with higher exposure to disasters extend more loans.[12] In addition, it shows that local lenders will not indiscriminately lend during disasters and rely on the soft information they collect.

I present evidence that access to local finance is less helpful when counties are more industrially or geographically concentrated. In such locations, business failures are more correlated and the idiosyncratic risk matters less. As a result, more community banks experience loan losses and have limited capacity to expand funding. I find that increasing access to local finance from the 25th to the 50th percentile limits contractions by half at industrially diversified counties and by less than a third in the rest. Local lenders have a smaller effect when activity is concentrated in the same census tract. In counties with more spatially dispersed activity, higher access to local finance (the 25th vs the 50th percentile) reduces contractions by a third compared to a quarter elsewhere. As with industrial concentration, when the pre-existing distribution of activity in a county leaves a subset of community banks unaffected by loan defaults, employment contractions are mitigated.

Evidence based on direct bank outcomes also supports the importance of idiosyncratic risk. Controlling for common county-level shocks, I am able identify the response of smaller, less diversified banks relative to the rest. I find that the average smaller community bank experiences lower direct loan loss and extends new business loans after hurricane impacts. Bigger banks within the county experience higher default risk, reduced payments on existing loans, lower net income, and a lower capital ratio. I do not find evidence that bigger local banks expand lending in counties with higher business losses. Consistent with the county-

[12] See Chavaz (2014); Cortés and Strahan (2017); Cortés (2014); Schüwer et al. (2019).

industry evidence, I conclude that smaller banks are likely to avoid direct losses and extend credit to businesses that are likely to remain profitable after reopening.

In the robustness 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. The rest of the paper proceeds as follows: section 2 discusses contributions and literature, section 3 details the construction of the data, section 4 considers the main impact of access to local finance, section 5 explores the factors behind the main effect of finance, section 6 includes robustness evidence, and section 7 concludes.

2 Related Literature

This paper intersects two distinct literatures that study: the local economic effect of natural disasters and the significance of local banking industry structure for local activity. Cortés (2014) examines the role of local finance during disaster recovery in the US and finds that local lenders increase credit by 0.1% in the impact quarter, generating 0.1%/1% faster total/young-firm employment growth. I retain the definition of local lenders and expand on several dimensions.[13] I test if local finance mitigates employment shocks specifically after hurricanes and focus on business damages, while controlling for residential loss.[14] I use monthly data for county employment by industry since hurricanes have opposing effects in different sectors (Guimaraes et al. (1993)) and the impact can dissipate quickly (Baade et al. (2007)). The granularity of the data allows me to devise a natural peer control group and limit the role of unobservable county heterogeneity. I further extend the sample of Cortés (2014), adding close to ten years of hurricanes and differentiate between costlier events. Finally, a big portion of this study is dedicated to explaining why community banks assist

[13] I classify lenders with over two thirds of deposits in one county as local. I use both the log of local deposit and the fraction of local deposits.

[14] While not the most frequent (only 20% of disasters), they cause the most severe damages (83% of total, Pielke Jr and Landsea (1998)) and present considerable challenges to community banks whose ability to recover from loan losses may be compromised by their geographic concentration (Emmons et al. (2004)).

in recovery. Similarly to Cortés (2014), I find that recovery improves with access to local credit. Differently from the paper, I find that only smaller community banks expand lending and that bigger ones experience significant deterioration in performance (face higher risk, reduced income, lower capital ratios). More generally, I find that when business losses are more correlated within the county local finance is less helpful with recovery.

A few other papers have examined the effect of local finance during disasters.[15] Koetter et al. (2019) studies the lending response of banks outside the direct impact of a river flood in Germany in 2013 but with existing business loans in the flooded areas. It finds that bank lending increases by 3%, affected businesses see a 16% increase in credit, and banks with lower geographic diversification see higher credit risk. Schüwer et al. (2019) documents that highly-capitalized independent banks extend new loans in their core markets after Hurricane Katrina. It presents evidence that counties with higher share of well-capitalized, independent banks experience faster employment growth two years after a hurricane. The share of independent banks is not, by itself, related to better employment outcomes. Several studies argue that banks are likely to expand lending after disasters.[16] Others show that banks are likely to restrict lending and in some cases this has negative effect on real outcomes.[17] Schüwer et al. (2019) examines the role of local lenders in employment recovery and explicitly considers the conditions necessary for community banks to assist with the recovery. My results are consistent with theirs as I show that banks with limited portfolio risk and limited capital ratio declines are the source of new lending to businesses in affected areas. I build

[15]For the literature on the effect of access to local finance in general see: Gilje (2019), Becker (2007), Ashcraft (2006).

[16]Chavaz (2014) studies how varying exposure to hurricane-generated losses during 2005 affects banks' supply of mortgage loans. The paper finds that banks facing wider exposure to affected counties also tend to expand lending more. Cortés and Strahan (2017) show that total mortgage originations increase by close to 3% above the normal in counties with disaster declarations related to all types of events during 2001 to 2010.

[17]Hosono et al. (2016) documents credit-supply reductions (and lower investment) at unaffected firms by banks affected by the Kobe Earthquake in 1995. Berg and Schrader (2012) argues that after volcanic eruption in Ecuador credit demand increases significantly but access to credit is improved only with an existing bank relationship. Garmaise and Moskowitz (2009) demonstrates that local banks are less likely to fund purchases of high earthquake risk properties after the Northridge earthquake in 1994. Berger et al. (2015) looks at the Great Recession and shows that access to local lenders is associated with more credit and lower failure rate for start-ups only during normal times (prior to the Recession) but not during the crisis.

on their results by documenting that bigger community banks experience drops in capital ratios and limit lending, as well as extending the sample to close to 20 years of hurricanes (they consider only 2005). I reconcile the mixed results in the literature regarding the role of smaller banks by showing that the incidence of loan losses across local lenders is key in explaining when access to finance helps with recovery.

The current study is also related to the extensive literature that examines the economic impact of natural disasters.[18] Only a handful of studies look at the universe of disasters and none of them cover the last 15 years included in my sample. Strobl (2011) examines the net growth impact of hurricane destruction in US coastal counties during the 1948-2005 period and finds a 0.45% decrease in at the county but limited impact at the state level. Deryugina (2017) studies the long-term impact of hurricanes in the US on population, earnings, and employment between 1979-2002, as well as the importance of government transfers during such events. Based on a difference-in-difference estimation on propensity-matched counties, the paper finds that employment rate is lower five to ten years after a hurricane, while earnings and population remain unchanged. Boustan et al. (2020) examines the long-term impact of a list of disasters in the US between 1918-2012, focusing on county-level migration and house prices, and finds an increase in out-migration and a decrease in house prices. My results complement these studies by focusing on the short-term, sectoral impact of hurricanes for an extensive sample of events. I show that the majority of the employment effect is short-lived and disappears after two quarters.[19] Importantly, I provide an explanation for the difference in the severity of employment contractions.

My results are largely consistent with the findings of case studies related to individual hurricanes. Belasen and Polachek (2008) shows that county employment decreases between 1.5% and 5% for two years after hurricanes in Florida during 1988-2005, using hurricane severity as treatment. It also examines industrial sectors and finds that manufacturing, trade, and finance are negatively impacted, while services are positively impacted. Guimaraes

[18] See Kousky (2014) for an extensive review of the literature.
[19] Cortés and Strahan (2017) shows this is also the case with mortgage lending.

et al. (1993) conducts a multi-sectoral analysis of the impact of Hurricane Hugo in South Carolina. It shows that while state employment was stable, construction increased by 8.5% at the expense of retail, trade, transportation and public utilities. Ewing et al. (2003) finds a decrease in employment growth after the Fort Worth tornado of 2008 in Texas. There was a heterogeneous response by industry with the trade sector experiencing significant decline. Meltzer et al. (2019) documents significant employment losses across the retail sector during Hurricane Sandy in New York City.

My paper is also related to the literature on the vulnerability of geographically concentrated community banks to local shocks. There is significant evidence that community banks have lower market risk exposure. Yeager (2004) identifies counties with shocks to unemployment during the 1990-1998 period and compares local bank performance to a matched unaffected peer, finding no statistical difference. Meyer and Yeager (2001) looks at local rural banks and finds that a range of performance measures (ROA, net loan losses, loan losses to total loans, etc.) are not related to the county's economic conditions captured by the unemployment rate, employment growth, personal income growth, among others. Emmons et al. (2004) argues that bank mergers which increase geographic diversification do not significantly improve the risk-return tradeoff for local banks, implying that they have lower exposure to local economic shocks. Aubuchon et al. (2010) examines the set of failed banks during the Great Recession and finds that slightly bigger commercial banks are more were more likely to fail. Considering evidence related to bigger, bank-holding companies (BHC), Stever (2007) argues that while smaller banks face higher idiosyncratic risk, due to their inability to diversify, they extend lower-credit risk loans or loans with higher collateral, which reduces their exposure to market risk. Demsetz and Strahan (1997) conclude that smaller banks are less diversified but not more risky. Deng et al. (2007) shows that cost of debt for small bank holding companies is impacted much less by geographic diversification compared to bigger banks, suggesting that smaller, concentrated banks are not seen as more risky by credit markets. I contribute to this literature by showing smaller banks are, on average, less likely to be affected during hurricanes, which allows them to provide funding during the rebuilding period. I document that local lenders do not improve recovery in markets where damages are more strongly correlated and even smaller lenders experience direct loan losses. I also show directly that, within the same market, smaller banks perform better and lend more during hurricanes.

3 Data and Sample Selection

This section describes some of the main data sources and discusses the definitions of the main shocks in the empirical model.

Hurricane Damages: I track US hurricanes between 1999-2019 using FEMA's list of major state-specific disaster declarations. Declarations are time-specific and include a set of affected counties. All data sources are linked based on FEMA's unique declaration number. When the declaration number is not available, as in the case of flood insurance, I use the date of the disaster to identify which losses are generated by each hurricane. [20] I use four distinct data sources to approximate county damages. With the exception of flood insurance, each of these is related to disaster relief programs: individual assistance by FEMA; business/residential loans by the Small Business Administration (SBA); public assistance by FEMA. However, this measure does not include all of the incurred losses. I cannot identify losses insured by business-interruption, home-owners, hurricane, or vehicle insurance.

The first data source is the SBA's dataset on verified residential and business damage. After each disaster, home or business owners can apply for low-interest loans, administered by SBA, to cover uninsured losses. For each applicant, SBA records the total loan amount requested and the total loss incurred, as well as the location of the property. Starting from the year 2001, the agency makes publicly available an aggregated version of its loan-level data at the level of the zip-code and city/county for each disaster declaration. Since the

[20] To identify whether a disaster declaration is related to a hurricane, I use FEMA's disaster-type classification. I have manually re-classified declarations of hurricane Lee and Dennis in states where they were listed as tropical storms.

non-public data includes both approved and denied applications with the corresponding verified loss (to real estate and to inventory/equipment), the public data provides a good approximation for the overall business and residential uninsured loss for everyone that has applied for assistance. In some of my preliminary analysis, I utilized a limited loan-level information attained through a Freedom of Information Act request. I am able to match this dataset to a subset of counties affected by 13 (out of 33) hurricanes between 2002 and 2012. The loan-level information lists the 6-digit NAICS industry code for each business disaster loan. I use this to identify which types of businesses are more likely to be affected by hurricanes and to limit my focus on a subset of industries in the main analysis.

The second data source comes from the FEMA's Individuals and Households Program (IHP). The program provides non-repayable grants to homeowners and renters to cover disaster losses. Payments are aimed at providing for immediate needs following disasters and to supplement other sources of recovery funds. The information for homeowners includes total property damage, determined by FEMA inspectors, and the amount of relief for each county and disaster declarations. For renters and homeowners the data lists the amount of rental assistance provided for households which are displaced. Property damage measures uninsured residential loss and the rental relief measures population displacement.

The third data source uses FEMA's Public Assistance (PA) data. The program provides grants to state and local governments to respond and recover from major disasters. The PA covers damage to roads and bridges, water control facilities, public buildings, and public utilities. It also provides funds for the necessary removal of debris and protective measures. I use the total amount of public assistance paid to each county after each disaster to approximate the amount of damage to the public infrastructure. I classify public loss as a component to business damages. It can be argued that public losses are a form of residential loss since they can lead to increased local taxes. At the same time, damage to public utilities and transportation infrastructure more directly limits business operations and can capture losses from business interruptions.

Finally, I use information on insurance payments from the National Flood Insurance Program. FEMA (the agency in charge of managing the NFIP) provides public information, at the census tract level, for flood-insurance claims, amounts paid, and the date on which the loss was incurred. I match the date of loss to the date of each hurricane event in each county to identify whether the insurance claim is related to a disaster. I classify insurance payments into business or residential based on the type of property.

All together, my measure of hurricane loss can be divided into business and residential loss. 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. Each component is specific to the county and disaster declaration, spanning the period between 1999 and 2019 or a total of 33 Hurricanes.

Table 2 lists detailed summary statistics for individual hurricanes and separates counties with positive business/residential damage. The distribution of damages varies significantly across the set of hurricanes: historical events, such as Katrina, Sandy, and Harvey cause significant loss both at the mean and in the tail; other hurricanes generate a majority of loss within a small set of counties, leading to significant loss in the tail. The correlation between business and residential damages is 0.72 and tends to vary with each hurricane. In the case of Katrina, Sandy, and Harvey the correlation is 0.83, 0.81, and 0.73, respectively. This highlights the importance of controlling for residential damages. Table 3 list summary statistics for business damage for individual states. It shows that hurricanes tend to be more frequent and generate higher losses in southern states. At the same time, hurricanes in the northeast while not frequent can lead to significant damages.

Economic Activity: The main empirical model focuses on employment growth at the monthly frequency for industry super-sectors. The data, at the county level, comes from the Bureau of Labor Statistics. It also includes counts of establishments and average weekly earnings, at the quarterly frequency, which are used in some extensions. The main sample starts from 1998 and runs through 2020.

Additional data for employment by establishment size and establishment age come from the Quarterly Workforce Indicators (QWI). The data is available quarterly and is aggregated at the county for each super-sector. For the majority of states the sample starts in 2000 and ends in 2018.

The main empirical analysis uses annual county GDP to deflate hurricane losses. I also use industry-specific GDP to define county-peer groups and to calculate an HHI index for industrial concentration by county. The data comes from the Bureau of Economic Analysis (BEA) and is available from 2000 to 2018. I use county data from 2000 to define county-peer groups for 1999 and to deflate losses from that year.

Measure of Local Finance and Bank Data: I measure access to local finance with the fraction of county deposits in local community banks. Following Cortés (2014), I classify as local banks institutions which have more than 65% of deposits located in one county (Meyer and Yeager (2001) uses 100%). The amount of deposits in the county where each local bank has the majority of its deposits adds up to the total local deposits. I use the amount of local deposits as a fraction of total county deposits as the main measure of access to local finance. Alternatively, I use the fraction/log of local banks and log of local deposits to also measure access to local credit. The information on local deposits comes from the Summary of Deposits (by FDIC). I use annual observations from 1997 to 2019 and construct measures of local finance based on the lagged value for each county. Finally, bank balance sheet data at the quarterly frequency comes from the Call Reports provided by the FDIC and linked to the credit data using the bank certificate number.

Definition of Hurricane Exposure: In order compare business losses across different counties and across time, I deflate the amount of absolute damage by the annual value of county output. Since counties with significant commercial activity are likely to experience higher absolute loss, comparing total damage provides a misleading picture of the extent to which businesses are affected. Instead, expressing losses in relative terms can proxy for the fractions of affected businesses, assuming that the distribution of losses within the county is not extremely skewed. It also allows us to compare hurricanes over the extensive time span. Counties with considerable output may also take more significant measures to protect businesses from hurricane damage or at least to insure against such losses. To limit the impact of local economic development on relative hurricane damage, on local access to finance, and ultimately on the recovery of employment, I form county peer groups based on the county's GDP decile within each state. The main empirical specification compares employment growth relative to a set of counties with similar level of commercial activity.

A county is classified as exposed to hurricane loss if it has a positive relative business loss. Some counties are subject to minimal loss and have relative loss approaching zero. I do not censor the relative loss in such counties but instead use them as a comparison group.

I control for residential loss using absolute residential damages relative to county GDP. This is motivated by the close association between earnings and output at the county level. Relative residential loss captures the proportion of households' annual income that is necessary to repair the damage to residential property. Furthermore, since counties with higher earnings, within the state, have more expensive real estate, this measure is also related to the fraction of real-estate value destroyed by a hurricane.

Sample Selection and Summary Statistics: The sample includes monthly observations of county employment growth (by industry super-sector) within a window of six months centered at the month of impact of each hurricanes between 1999 and 2019. I only consider counties, within each affected state, with positive business damage and exclude those which are either completely unaffected or have only residential damage. Since some counties in Louisiana and Mississippi where severely affected by Hurricane Katrina, I also exclude: Orleans Parish, St. Bernard Parish, and Hancock County. Relative damage for each approaches 100%. Table 1 compares summary statistics for states hit by hurricanes by separating counties based on business loss and access to local finance. In each case the means are for the month of impact of each disaster. It is notable that counties with no business loss also have limited residential loss. As a result, focusing on counties with business damage captures the full impact of each hurricane within each state. Damage incidence is slightly higher for homeowners compared to business owners (0.85% residential vs 0.63% business damage). Damages to public infrastructure make up the biggest component of business loss (60%) and can explain why residential and business losses are closely matched. It is also interesting to note that the proportion of insured loss is only 5% for businesses and 41% for homeowners.

The analysis focuses on a subset of industry super-sectors since losses are likely industry-specific (Webb et al. (2000), Guimaraes et al. (1993)). I exclude Natural Resources and Mining because my measure of losses does not directly capture agricultural or mining damage. I also exclude Construction since necessary repairs after hurricanes generate increased construction employment in most locations but are not indicative of broader economic recovery. I identify industries which are likely to be directly affected using a limited dataset of SBA disaster loans (described above) which list the industry code for each borrower. Table 1 shows that the highest fraction of disaster loans go to the Financial Activities super-sector. Decomposing by 4-digit NAICS industry codes shows that the majority of businesses are related to commercial rental activities and suggests that this category includes damages to properties which are rented to other businesses. The sectors of Trade-Transportation-Utilities, Leisure-Hospitality, and Other Services are particularly vulnerable to hurricanes incidence and constitute 40% of all disaster loans. Hurricane studies also tend to find negative employment effects primarily in these sectors (Belasen and Polachek (2008); Guimaraes et al. (1993); Meltzer et al. (2019)). The main analysis in the paper focuses on these three sectors with the addition of Professional-Business Services and Manufacturing.

4 Local Finance and Employment Recovery

I identify the role of local finance on employment recovery by relying on within-state variation in the extent of business losses and in the access to local finance facilitated by the presence of community banks. The average (median) hurricane in the sample affects 42% (31%) of the counties in a state.[21] The average (median) hurricane causes more than 0.5% of business damage in 4% (0%) of the counties. As a result, losses to businesses can vary substantially. In the case of events with more substantial losses, such as Katrina, Sandy, or Irma, more than 90% of the countries were affected. Still, approximately 10% of states' counties experience business losses over 0.5%. The geographical distribution of business losses within each state suggests that focusing only on affected counties will provide sufficient variation in losses to identify the initial decline in employment and subsequent recovery.

The effect of hurricane damage on the local economy is evident in the sample averages from Table 1. Counties without losses have monthly employment growth of 0.13%, while those with positive damage experience employment contraction of 0.65%. The effect on employment is driven by establishments with less than 20 employees. Quarterly employment at small businesses falls by 1.22% in affected counties (0.28% for no loss counties). Hurricanes lead not only to closures of existing business but also create opportunities for new ones – employment growth at newly-founded establishments (less than 3 year old) is 0.92% in counties with losses compared to 0.48% at those without. Comparing employment growth during the month of impact and the average over the quarter reveals that counties experience most severe contractions right after hurricanes and limit the initial contraction fairly quickly.

In order to examine if access to local credit makes a difference in the recovery process, there needs to be sufficient variation in the structure of the local banking industry which is not related to the vulnerability of local businesses to damages. In principle, community banks may avoid establishing branches in counties susceptible to hurricane loss, leading to higher access to local credit in counties with lower losses in the sample. In this case counties with higher access to local finance may recover faster not due to the local banking structure but because of the lower damage. Table 1 shows that this is not the case. The fraction of deposits held in local banks in counties without/with damage is 25.9%/23.2%. Comparing

[21] The sample includes 117 state-hurricane observations. To be counted as affected a county has to have positive business damage.

alternative measures of access to local finance such as the number of local banks, the share of local banks, the log of local deposits also confirms that business damages are not related to the underlying banking structure.[22]

Table 1 shows that the average county with business damage contracted employment by 0.65%. Splitting affected counties based on the median fraction of local deposits (last four columns) shows that access to local finance improves employment recovery. During the month of hurricane impact, employment contracts on average by 0.8% in counties below the median compared to 0.5% in those above. The positive effect can be seen in the average employment growth for both small and young businesses. Note that the two groups experience similar average damages (approximately 0.6%) and have similar industrial composition on a variety of dimensions. This confirms that community banks are not more or less likely to be located in counties with significant damage.

Empirical Methodology

The main empirical strategy in this paper is based on an event-study specification. I focus on monthly employment growth for a set of industries during a short period before and after the hurricane shock. Figure 1 plots average employment growth for counties with business damage above/below 0.5% for each of the five months before and after the impact. In the run-up to the shock both groups follow a similar trend. During the month of the impact areas with damage exceeding 0.5% experience significantly bigger contraction in employment (-2.2% vs -0.8%) which persists in the next month and is followed by a recovery in the second month after the shock. Figure 2 further breaks down the dynamic response of this group based on the median access to local finance. Counties with lower access experience significantly deeper contraction on impact (-2.5% vs -1.6%) and show a marginal recovery. In contrast, areas with more local banks not only contract less on impact but also experience much stronger recovery. The evidence supports the hypothesis that the presence of community

[22]Counties with more than 0.5% in damage also have similar average fraction of local deposits (20%) compared to those with lower damage (23%).

banks improves the recovery following damage to businesses. It also shows that the majority of the impact, on average, occurs within the first quarter. This is consistent with the findings in Strobl (2011) that hurricanes have no impact in the year after the impact. Consequently, I further restrict the window of the event study to three months before and three months after the impact (including the impact month).

To formally test the effect of local finance, I focus on employment growth by industry in each county, controlling for the amount of residential damage and possible relocation of residents, allowing for common industry shocks across counties in the same peer group, and controlling for local economic development.[23] The sample includes three months before/after the hurricane impact for counties with positive business damage, starting with the first hurricane in 1999 (Bret) and ending in 2019 (Harvey/Dorian). The graphical evidence showed that the weather shock causes, on average, two consecutive contractions and a recovery. I summarize the dynamic response by estimating the average employment growth during the three months after the weather shock and focus on the difference in this response due to access to local finance. The main specification is:

$$\begin{aligned}\triangle \ln \text{Employment}_{i,c,m} &= \beta \text{DamageBusiness}_{c,(m,m-2)} + \psi \text{DamageBusiness}_{c,(m,m-2)} \text{LocalFinance}_{c,(m-12)} \\ &+ \gamma \text{LocalFinance}_{c,(m-12)} + \beta_2 \text{DamageHousehold}_{c,(m,m-2)} + \eta Z_{i,c,m-12} + \alpha_{i,c} + \gamma_{i,st(c),m} + \epsilon_{i,c,m}\end{aligned} \tag{1}$$

where $\triangle \ln \text{Employment}_{i,c,m}$ is the time difference in the log of employment in super-sector i, in county c, during month m. I also estimate this model using employment by businesses with less than 20 employees or employment by each industry. $\text{DamageBusiness}_{c,(m,m-2)}$ is relative business damage in county c during a hurricane impact in month m or up to two months after the impact. In some specifications, I further break down the sample by the

[23] As discussed in the data section, I exclude Natural Resources and Mining, Construction, Financial Activities, Information, and Education and Healthcare. I further exclude industry-county observations if median total employment is below 100.

overall business damage in a given state in order to estimate the impact of costlier hurricanes. $\text{LocalFinance}_{c,(m-12)}$ is the fraction of county deposits held in local banks twelve months before m. I also report results for three alternative measures of access to local finance: log of deposits held in local banks, fraction of local banks, log of total local banks. $\text{DamageHousehold}_{c,(m,m-2)}$ is relative residential damage in c during an impact in m or up to two month afterwards. $Z_{i,c,m-12}$ includes a vector of four industry-county-specific variables and two county-specific ones (each centered at the sample mean). The first set includes industry-specific log output, log labor productivity, fraction employed by small businesses (less than 20 employees), fraction employed by young businesses (less than 3 years).[24] The second includes a measure of population displacement based on the dollar amount of rent grants (as a fraction of total county income) and a measure of the county's industrial diversification based on the HHI index of super-sector GDP shares (out of total county GDP). $\alpha_{i,c}$ is a super-sector-county fixed effect. $\gamma_{i,st(c),m}$ is a non-parametric industry-state trend. In less restrictive specifications I replace this trend with an industry-county-group one. I designate county-industry peer groups within each state based on relative output: county-group-4 assigns as peers counties with industrial output in the same quartile; county-group-10 does this based on the decile. Since the dependent variable reflects employment growth, the fixed effect in the specification accounts for differences in the trend of employment across industries in counties. $\gamma_{i,st(c),m}$, accounts for common shocks at all the counties in a state or at counties with a similar level of industrial output, i.e. the same quartile/decile.

The coefficient of interest in this specification is ψ. It quantifies the difference in the effect of business damage across counties with varying access to local finance. The inclusion of the industry-county-group-month effects implies that the coefficient is identified by comparing employment at counties with similar industrial output, holding both business and residential

[24]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 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.

damage constant. The identifying assumption is that, with the exception of the presence of local community banks, the counties in the same peer group share the same underlying economic characteristics and are likely to respond in a similar way to hurricane losses (hence they share the same employment shock). Since peer groups are based only on relative industrial output, which may not capture the full set of differences between counties, I further control for industry-specific output, labor productivity, proportion of small/young businesses, as well as population displacement and industrial diversification. Under this specification the coefficient will not be identified if a hurricane affects two counties with significantly different industry output levels, e.g. a rural and an urban county.

Results

The evidence from specification (1) consistently shows that increased access to local finance – measured by the fraction of deposits held by local banks, the log of local deposits, or the fraction of local banks – dampens the employment contraction resulting from business damages. This applies to the average industry in affected counties, to each sector on its own (with the exception of manufacturing), and has a particularly strong effect on small businesses (with less than 20 employees). Community banks help local economies avoid employment loss not only during less costly events (below $1 bil. at state level) but also when damages are substantial.

Estimates of model (1) for monthly employment growth are provided in Table 4. Column (1) lists the most basic specification that includes only a county-industry fixed effect. Columns (2)-(5) introduce county-industry controls and sequentially allow for a less restrictive specification of the local industry employment shocks: at the national, state, county peer group based on industry output quartile, and county peer group based on the decile of industry output. I illustrate the marginal effect of LocalFinance by providing an estimate of the effect of business damage at the 25th, 50th, and 75th percentile of LocalFinance. I use a hypothetical 1%-damage-event to compare the effect of access to local finance.

Column (1) shows a negative and significant effect for business damages and a positive and significant interaction with LocalFinance, implying that higher county losses depress employment growth more strongly in places with lower access to community banks. The implied reduction after a 1%-loss-event is 0.24% with lower presence of local lenders (at the 25th percentile), 0.15% with medium presence (at the 50th percentile), and there is no reduction with high presence (at the 75th percentile). The 0.24% reduction in the employment outcome for places with limited access to local finance is significant in magnitude – it is close to one standard deviation of employment growth for counties without damage. Residential damage has a negative and (marginally) significant direct effect on employment. This is consistent with recent findings (Xiao and Van Zandt (2012)) that the negative household wealth shock can depress local activity even with minimal business damage. The effect of population displacement is negative but only significant in the sample of costlier events (over $1 bil. at state level), where a bigger portion of the county's population may be relocated.

Identifying the effect of local finance requires that BusinessDamage and LocalFinance are not correlated with other factors at the county. Businesses can relocate away from counties with regular hurricane incidence or develop protective infrastructure. Adjustments to prospective weather shocks can vary by the industry sector, the relative productivity of local firms, or the endowments of the local economy.[25] The local banking structure can also respond indirectly to anticipated future damages by co-relocating with business.

I address this by directly controlling for differences in characteristics of an industry across counties. In this case, if counties with lower industry output tend to receive higher business damage because firms do not expand in vulnerable places, the correlation between damage and output will be accounted for by the industry GDP control. The interpretation of business damage and its interaction with local finance is the effect after holding GDP, and its impact on damage, constant. The same consideration holds after including each of the three other county-industry specific controls. Column (2) provides estimates with the additional

[25] For example, the hospitality sector may find it appropriate to locate to places with higher exposure to weather shocks, while manufacturing will do the opposite.

controls and confirms that direct business damages and access to local finance preserve their magnitude and significance. This suggests that the hurricane impact is less predictable than expected, as argued by Belasen and Polachek (2008), or that businesses/lenders do not actively anticipate disasters, unlike Garmaise and Moskowitz (2009).

Including a set of industry-county characteristics helps limit some of the possible relationships between county factors and incurred damages. Yet, this is far from an exhaustive list of potential factors. I further control for unobservable heterogeneity between county-industries by forming relative-output peer groups and identify the main effect based on within-group variation. For example, in this case, the recovery of a big hospitality-sector-county is only compared to that of a county where hospitality is similarly represented. This ensures that all of the unobservable factors which enable the development of such industry in both counties are similar. Results in Columns (3), (4), and (5) sequentially relax the definition of a peer group to all county-industries in the same: state, output quartile, output decile. Estimates in each case are similar and consistent with the baseline estimation without peer groups. Note that the sample in Column (5) is the smallest since it drops affected county-industries without any peers. This estimation also shows the highest impact of access to local finance – after a 1%-loss-event employment growth falls by 0.25% with lower presence of local lenders (at the 25th percentile), by 0.15% with medium presence (at the 50th percentile), and does not fall with high presence (at the 75th percentile).

Hurricanes can vary significantly by how much damage they generate in individual states (Kousky (2014)). I classify state events into more or less costly ones based on a $1 bil. state-damage cutoff, in order to examine if local finance plays a different role in recovery after bigger shocks. The estimates in Column (6) are similar to my preferred specification in Column (5). At the same time, estimates for less severe hurricanes in Column (7) also suggest that local lenders help in recovery.[26] This suggests that identification is driven by both types of hurricanes.

[26]The main coefficients of interest are bigger in magnitude owing to the significantly smaller damage during the less costly events.

In Columns (8), (9), and (10) I test the robustness of the results to alternative measures of access lo local finance. With the exception of the last estimation, using the log of total local lenders, the estimates remain consistent with the main evidence: industries in counties with lower access (at the 25th percentile) experience approximately one standard deviation lower employment growth compared to those with higher access (at the 75th percentile).

Table 5 examines the heterogeneity of the baseline results by industry sectors. I also consider a different data source/employment outcome. The first two columns use establishment growth (from BLS) and employment by firms with less-than-20-employees (from QWI) as dependent variables.[27] The results show that while the count of establishments may not be affected by business loss, the total employment at these establishments decreases with more significant damage. Access to local lenders appears to be particularly helpful in reducing the employment contraction at these smaller businesses. A 1% damage event leads to 0.95% lower employment growth in counties at the 25th percentile of LocalFinance compared to those at the 75th percentile. This represents about one standard deviation change in employment growth for small businesses.

Columns (3) through (7) are based on samples of individual industry sectors. With the exception of manufacturing, each sector experiences employment contractions which are tempered by higher access to local lenders. The lack of response in manufacturing mirrors previous findings by Belasen and Polachek (2008). The Hospitality sector is most strongly affected by direct losses, followed by Other Services, and Trade, Transportation, and Utilities sectors. Access to local finance has the strongest positive effect in the case of Professional services, followed by Leisure/Hospitality, and Other Services. The existing literature unequivocally documents that the Trade/Transportation/Utilities and the Leisure/Hospitality sectors are negatively impacted by hurricanes.[28] I not only confirm these results but also show that access to local finance can explain the variation in the extent of the impact across

[27]Each of these observations are reported quarterly. As a results, business damage represents hurricane loss that occurs during the reporting quarter.

[28]See Belasen and Polachek (2008); Guimaraes et al. (1993); Meltzer et al. (2019).

different hurricanes and counties.

All together, the evidence consistently shows that the presence of local lenders is associated with lower employment loss. Direct damages often lead to revenue shortfalls either because they prevent businesses to function properly or drive away consumer base. Without revenue (or personal savings), owners have to rely on credit to restore their business and bring back employees. My results suggest that local lenders provide such credit, while more distant or national ones do not. This results in a substantial difference in the employment outcomes across counties with varying access to local finance.

The evidence so far does not directly indicate that local lenders extend additional loans in affected counties. It also does not discuss how local lenders are able to avoid losses to their existing loan portfolio, which can limit the capacity for new credit. The next section sheds light on their role in identifying businesses that can remain profitable after reopening and on the factors that allow local lenders to avoid direct losses.

5 Why Community Banks Help with Recovery?

I test two distinct but complementary factors that can explain why community banks are able to alleviate the employment shock of hurricanes and improve recovery.

Empirical Methodology

First, due to their proximity to local businesses (Agarwal and Hauswald (2010); Degryse and Ongena (2005)) and specialization in lending to firms with limited financial track record (Berger et al. (2005)), community banks are uniquely positioned to identify businesses able to repay loans if they reopen (Basker and Miranda (2018)). In locations where the number of such businesses is small, local finance should have a lower impact on recovery. Second, since community banks have less clients they are exposed to lower market risk and, instead, face more idiosyncratic risk, tied to the fortunes of individual borrowers. Examining merger, Emmons et al. (2004) concludes that market risk is not deemed important for managers of community banks since most mergers combine lenders in the same labor market.[29] The lower exposure to correlated losses within the county (market risk) and more prudent lending can makes it more likely that the average community bank can avoid defaults on existing loans and expand credit to businesses. If losses are more strongly correlated within counties even lenders with lower exposure to market risk will face defaults and limit additional lending. I examine if this is the case by focusing on counties where most businesses are concentrated in the same industry or census tract (Gunther et al. (1999)). I also test directly if smaller banks within the same county tend to perform better and lend more than bigger banks, which are more likely to be exposed to local market risk. Both the ability to identify productive businesses and avoid loan losses are required for local banks to help with the recovery.[30]

Approach I: County Outcomes

In the first one, I extend the baseline model to a triple-difference one. I examine how the effect of access to credit changes across counties with higher labor productivity, higher industrial concentration, or higher geographic concentration. Hurricane loss generates significant direct and indirect cost for businesses (Kroll et al. (1991)) which can only be repaid by more productive ones (Basker and Miranda (2018)). If community banks enable more productive businesses to survive hurricane losses, access to local finance should have a stronger effect in counties with higher productivity.[31] Community banks are also less sensitive to local market conditions (Yeager (2004)) and are, instead, exposed to defaults by specific borrowers (driven by firm-specific factors). Furthermore, they compensate for their limited diversification by extending lower-credit risk loans or loans with higher collateral (Stever (2007)). Both make the average community bank less likely to be directly affected by losses on its loan portfolio.

[29]This assume that managing distant offices is not significantly costlier.

[30]I also implicitly test that banks are willing to lend in locations with increased disaster risk. Garmaise and Moskowitz (2009) shows this is not always the case.

[31]This effect is distinct from from the direct effect of productivity (included in my specification) which helps more productive counties to recover faster.

As business losses become more correlated within the county, idiosyncratic risk matters less and more community banks may be exposed to losses. I test the importance of idiosyncratic risk as a way for community banks to avoid market-level shocks, by focusing on counties where loan defaults are likely more correlated – areas where activity is concentrated in the same industry or census tract. A bigger role of local finance in counties with less correlated defaults (less concentrated counties) is consistent with the interpretation the community banks help recovery by having limited losses during hurricanes.[32]

For the first approach, I estimate the following specification:

$$\begin{aligned}\triangle \ln \text{Employment}_{i,c,m} &= \beta \text{DamageBusiness}_{c,(m,m-2)} + \psi \text{DamageBusiness}_{c,(m,m-2)} \text{LocalFinance}_{c,(m-12)} \\ &+ \eta \text{DamageBusiness}_{c,(m,m-2)} \text{LocalFinance}_{c,(m-12)} \text{X}_{i,c,(m-12)} + \gamma \text{LocalFinance}_{c,(m-12)} + \gamma_2 \text{X}_{i,c,(m-12)} \\ &+ \psi_2 \text{DamageBusiness}_{c,(m,m-2)} \text{X}_{c,(m-12)} + \gamma_3 \text{LocalFinance}_{c,(m-12)} \text{X}_{i,c,(m-12)} \\ &+ \beta_2 \text{DamageHousehold}_{c,(m,m-2)} + \zeta Z_{i,c,m-12} + \alpha_{i,c} + \gamma_{i,st(c),m} + \epsilon_{i,c,m}\end{aligned} \tag{2}$$

where $\text{X}_{i,c,(m-12)}$ is an indicator for higher labor productivity, industrial concentration, or geographic concentration. Labor productivity is measured by industry-county-specific lagged average weekly earnings. For each industry, the indicator includes all counties with above median (state) earnings. Industry concentration is measured by the HHI index of GDP shares of all industry super-sectors in a county. I use the state median industry concentration to assign counties to the high-concentration category. Geographic concentration is based on the share of total county employment located in the census tract with the highest employment.[33] Counties are classified as having higher geographic concentration if the employment share in the top census tract is more than three times the share if employment is equally distributed

[32] High geographic concentration implies that a weather shock will cause losses to all of the businesses in a county and will lead to portfolio losses for most community banks.

[33] Census tract employment shares are based on data from Census's Longitudinal Employer-Household Dynamics Data

across all tracts.

The model extends equation (1) by interacting $X_{i,c,(m-12)}$ with business damage, local finance, and their interaction. The coefficient of interest, η, explores a triple-difference outcome of whether access to local lenders provides a stronger/weaker help with employment recovery depending on the productivity or concentration of the county. Since the model includes $\text{DamageBusiness}_{c,(m,m-2)} X_{c,(m-12)}$, which controls for the direct effect of $X_{i,c,(m-12)}$ on affected counties, η captures the effect of $X_{i,c,(m-12)}$ through local finance. For example, in the case of above-median productivity, ψ_2 identifies the difference in employment recovery for more productive counties, while η reflects the difference in recovery for productive counties with higher access to local lenders. If higher productivity, on its own, can explain how employment responds to hurricane losses, η will not be significant and ψ_2 will be. If productivity matters specifically in counties with access to local finance η will be significant.

A positive estimate of η when $X_{i,c,(m-12)}$ is an indicator for above-median labor productivity implies that community banks improve hurricane recovery by identifying and lending to more productive establishments. Conversely, the mere presence of community lenders cannot help reduce the employment impact of hurricanes in the absence of firms productive enough to repay the additional costs. Note that this effect is in addition to the ability of more productive industries to recover regardless of local finance, captured by ψ_2.

A negative estimate of η when $X_{i,c,(m-12)}$ is an indicator for above-median geographic or industrial concentration indicates that local finance has a limited impact on recovery. It is consistent with the interpretation that community banks help with recovery in counties where loan defaults are less correlated and lenders can avoid a deterioration in the quality of their loan portfolio. This is more likely to be the case in areas with a more diversified or spatially spread out local economy. Conversely, most community banks operating in counties with concentrated (spatially or by industry) activity will experience similar deteriorations, limiting their ability to support local businesses.

Approach II: Bank Outcomes

In the second approach, I focus directly on the lending activity and the quality of the loan portfolio of community banks after exposure to hurricane losses. I compare outcomes for bigger banks (still located in one county), which diversify risk from defaults of individual borrowers and have higher exposure to local market risk, to those of smaller banks, which have higher exposure to idiosyncratic risk (Yeager (2004)). The approach is similar to identifying the effect of local finance across counties with varying geographic/industrial concentration – high concentration increases the correlation of business losses and limits the importance of idiosyncratic risk, causing more community banks to experience similar portfolio deteriorations. The identification in this approach relies on the assumption that the level of idiosyncratic risk varies with the size of the local bank, while the demand for credit does not. Given that the sample includes only relatively small independent banks with the majority of deposits within the same county, this is likely to be the case.

I use within-county variation in the responses of community banks to further support the hypothesis that local banks improve recovery because they are mostly exposed to idiosyncratic risk and, on average, avoid losses after hurricanes. This is not to say that community banks are not affected by weather events but that smaller banks will on average tend to have better quality of the loan portfolio since they are less diversified/exposed to the overall market risk. Because they also have superior information about local businesses, compared to nonlocal banks, they are in a better position to improve employment recovery.

The sample is based on quarterly observations on lending, loan loss allowance, risk-based capital ratio, net interest margin, and net income for local banks in counties with business damage. I follow a similar event-study setup, focusing on a period of two quarters before a hurricane and the impact quarter. For example, an August hurricane is matched to the third bank-reporting quarter (the impact quarter) and also includes the first two reporting quarters. As in Schüwer et al. (2019), the sample includes community banks used to calculate the LocalFinance 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.[34] 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. Wheelock and Wilson (2001) suggest that \$300-\$500 mil. is the optimal efficient scale of operation. I assume that at this scale community banks achieve sufficient diversification of idiosyncratic risk. I test whether these lenders experience lower portfolio deterioration and expand lending after weather shocks with the following model:

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

where $Y_{b,c,q}$ refers to an outcome for local bank b, located in county c, during quarter q; $\text{SmallBank}_{b,(q-4)}$ is an indicator for a lender with assets below \$300 mil.; $\text{DamageBusiness}_{c,q}$ is the relative business damage during the quarter of impact. $W_{b,q-4}$ includes a vector of bank controls: 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. α_b is a bank fixed effect and $\lambda_{c,q}$ is a county-quarter fixed effects.

Saturating the model with county-quarter fixed effects accounts, non-parametrically, for a common county-level shock that affects all lenders in a county, such as a change in the demand for credit. This allows me to identify the response of the smaller banks relative to the rest and helps distinguish whether the former tend to do better after hurricanes and expand lending to local businesses. The coefficient of interest, β, is identified under the assumption that both sizes of local banks are exposed to the same county-level shocks. In the case of lending, this implies that small and big community banks lend to the same type of local businesses.

[34] 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.

Results

County Outcomes: Estimates from specification (2) are listed in Table 6. For ease of comparison, Column (1) shows the baseline results using the full set of county-industry-specific controls and peer groups based on the decile of industry output. Both the controls and peer-group specification are retained in the rest of the table. In Column (2), I interact the indicator for high productivity with business damage and its LocalFinance interaction (as well as with LocalFinance). The effect of business damages is negative and significant, while its interaction with LocalFinance is no longer significant. The triple interaction with HighProductivity is positive and significant. This indicates that access to local finance is only helpful in counties with more productive businesses. The bottom of the table presents the marginal effect of business damages on employment growth for various levels of LocalFinance, separated for counties with different productivity. In low-productivity counties, local lenders do not improve the recovery: a 1% loss event reduces employment by 0.14%/0.06% at low/high access to finance. As discussed above, the difference is not statistically significant and we cannot rule out that the observed decline is the same. In high-productivity counties, access to local finance leads to stark differences in employment outcomes: a 1% loss event reduces employment by 0.4%/0.02% at low/high access to finance. This suggests that local lenders do not simply provide funding to all businesses in affected counties but mostly to those likely to survive after hurricanes.

Column (3) provides estimates using the indicator for high industrial concentration. The effect of business loss is negative and significant, its interaction with local finance is positive and significant, and the triple interaction with concentration is negative and significant. This suggests that access to local finance has a much stronger effect in counties with diversified economies.[35] The bottom of the table shows that both diversified and concentrated counties experience 0.3% reduction in employment growth with limited access to local finance.

[35] The specification already includes an interaction of concentration with damage (not significant) and so the effect of local finance is not due to diversified economies recovering faster on average.

Increasing access from the 25th to the 50th percentile limits the contraction in half at diversified counties and by less than a third. As underscored by the average disaster loan claims in Table 1, industry sectors vary in the extent of losses incurred by hurricanes. Consequently, a set of community banks will remain unaffected in diversified counties and can help reduce the employment contraction.

The evidence in column (4) looks at the effect of geographic concentration. Similar to industrial concentration, clustering of activity within the county can lead to similar losses for the majority of businesses and, by extension, to loan defaults for most of the local lenders. The estimates are consistent with those for industrial concentration. Access to local finance has a much smaller effect on the recovery when activity is concentrated in the same location. In counties with more evenly dispersed activity, having higher access (the 25th vs the 50th percentile) reduces employment contraction by a third, while in more concentrated counties the reduction is about a quarter. As with industrial concentration, when the pre-existing distribution of activity in a county leaves a subset of community banks unaffected by loan defaults, the local economy experiences a lower contraction.

The specification in column (5) includes all three indicators. The estimates retain their magnitude and significance, which suggests that productivity and each type of concentration capture a distinct factor that can explain the baseline effect. The extended specification allows me to estimate the effect of each indicator holding the rest constant. For examine, I can focus on the effect of local finance across counties with different productivity but with low industrial and geographic concentration. Lower concentration limits loan defaults for community banks and maximizes the impact of local finance. At the same time, lower productivity is expected to reduce this effect. The estimates at the bottom of column (5) are based on this scenario. In this case, even counties with lower productivity experience a positive effect from local finance but the magnitude is much smaller compared to high-productivity counties. This examine highlights that community banks help with recovery both because they are able to identify more productive business and they are less likely to experience losses in their loan portfolio.

Bank Outcomes: To provide direct evidence for the effect of hurricanes on bank lending and performance, I estimate model (3) with the sample of local banks in affected counties. Table 7 presents summary statistics for this sample and allows for a comparison between smaller (below $300 mil.) and bigger community banks. Just by comparing averages, we see that smaller banks, on average, have higher loan growth and a lower loan loss reserve ratio (over loans) during the quarter of hurricane impact.[36] This is in line with the interpretation of the evidence so far that community banks improve recovery by avoiding direct losses to their portfolio.

Table 8 presents estimates of specification (3). The first seven columns are based on within-county identification with county-quarter fixed effects, while the second seven columns use county peer groups (using the quartile of county GDP). As discussed above, including county-quarter effect allows me to estimate the impact of damages on outcomes for small banks relative to bigger ones. When I use county peer groups, the outcomes for both bank types can be identified. Column (1) shows that small community banks have lower risk of loan defaults compared to bigger ones when county damage is higher. In a 1%-damage-event small banks have 5 basis points lower risk reserve ratio. This magnitude represents approximately 10% of the standard deviation for this outcome. The estimates in column (8) imply that smaller banks also see an increase in risk and adjust their loss reserve but the effect is minimal. Besides higher risk of loan defaults, community banks can also experience reduced payments on existing loans. This will reduce net interest income growth and ultimately lower net income. The results in columns (2) and (3) confirm that small banks do better on each of these outcomes. During a 1%-damage-event, they experience 0.5% higher net interest income growth and approximately 0.1% higher net income over loans.[37] The estimates in columns (9) and (10) suggest that the relatively better position of small banks during hurricanes is

[36] The faster growth of the Loan-loss reserve for small banks is consistent with their faster loan growth.
[37] 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.

driven by the decline in net (interest) income at bigger banks. The overall deterioration in the performance of bigger banks can be inferred from columns (4) and (11), which focus on the risk-based capital ratio. In a 1% damage event, small banks have 0.08% higher Tier2 Capital Ratio. This appears to be driven by a small decline in the ratio for small banks and a much more substantial decline for bigger ones (based on column (11)).

The deterioration in the loan portfolio of bigger banks is likely to limit their ability to expand loans to businesses with damages (Accornero et al. (2017)). I find consistent evidence that this is the case. Columns (6)-(7) examine the growth of total loans, commercial and industrial loans, and loans to individuals. I also experimented with loans secured by commercial real estate and total loans secured by real estate and found consistent results. At smaller banks, a 1%-damage-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. Column (12) confirms that the difference in total loans is due to faster growth at small and no change at bigger banks. In the case of CI loans, Column (13) implies that bigger community banks expand business lending but at slower rate than smaller ones. The faster growth for loans to individuals in column (7) is explained by a significant reduction at bigger banks indicated in column (14).

The evidence indicates a consistent difference in the quality of the loan portfolio and lending behavior at community banks as counties experience higher businesses loss. The average small bank shows limited impact from loan defaults by businesses. In contrast, the average bigger community bank faces higher default risk and lower repayment rate in its existing portfolio, which is reflected in the increase in the loan-loss reserve and the reduction in net interest income. The increased cost due to the provision for loan loss and the reduced income from loan repayments amount to lower net income and capital ratio. As a result, bigger banks focus on existing loans when counties are impacted by a hurricane and limit the amount of new loans (Accornero et al. (2017)). In such locations, smaller banks take the lead in providing funds for local businesses as they experience much lower direct loss from affected businesses. Even though both bank types are concentrated in one county (with more than 2/3 of their deposits), their relative size difference makes the bigger ones more exposed to local market risk (Emmons et al. (2004)) and increases their odds of seeing direct loan loss associated with hurricane business damage. Smaller banks, instead, have higher exposure to idiosyncratic risk, which can either completely wipe out their loan portfolio and eliminate their lending capacity or leave them unaffected after significant business damage in the county. The evidence indicates that the average small community bank expands lending to businesses and experience lower direct loss to existing loans.

The two sets of evidence in this section, based on employment and on lender outcomes, point to two main factors which work together in explaining the baseline results. First, local lenders have a higher capacity to identify local businesses which can remain profitable after reopening and are likely to extend funding to them. There is a significant amount of research that already shows that local lenders focus on small businesses. The case of hurricanes does not directly apply to the existing literature because community banks can revise their assessment of risk involved in lending to businesses in areas prone to weather shocks, as in Garmaise and Moskowitz (2009). My evidence suggests that this is not the case. Even though businesses in more productive counties are less likely to reopen, when more local lenders are present contractions in employment are limited.

The second factor explains how 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 economies with higher industrial or geographic diversification. Such economies 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, while smaller ones expand business credit.

6 Robustness

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 9. 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.

7 Conclusion

In this paper, I consider both whether small lenders on average mitigate the negative employment shocks associated with hurricane damage to businesses and also identify necessary conditions allowing these lenders to assist in the recovery. I build a novel dataset that includes 33 hurricanes from the last 20 years and distinguishes between losses to residential and commercial property. The evidence is based on an event-study model of monthly employment growth by industry in each county, allowing for common county-industry shocks across the same peer group and directly controlling for county-industry characteristics such as output, productivity, and fraction of small/young firms. I also examine bank-level outcomes following a similar setup which controls, non-parametrically, for common county-level shocks.

The evidence consistently shows that increased access to local finance dampens the employment contraction resulting from business damages. This applies to the average industry in affected counties, to each sector on its own (except manufacturing), and has a particularly strong effect on small businesses. The results support the hypothesis that community banks help in the recovery by both being able to identify businesses with potential to survive and by avoiding direct loss to their existing portfolio of loans. The first factor explains why national banks may find it hard to step in during such disasters and the second explains why local banks are able to lend more.

This study contributes to the existing literature on natural disasters, access to local finance, and on the vulnerability of community banks to local shocks in several ways. I test if local finance helps with recovery from some of the costliest hurricanes in the US history and identify the effect specifically of commercial damages. The industry-based analysis allows me to devise a natural peer control group and limit the role of unobservable county heterogeneity. A big portion of this study is dedicated to explaining why community banks are able to assist in the recovery and, as a result, builds on existing evidence of the positive effect of local lenders. I reconcile the mixed results in the literature regarding the effect of hurricanes on the local economy by showing that the incidence of loan losses across local lenders is key in explaining why some areas recover quickly and others experience prolonged stagnation.

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
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 Financial Activities 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
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: 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.

VARIABLES	(1) N	(2) mean	(3) p75	(4) p90	(5) 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 4: Access to Local Finance and Industry Employment

This table provides estimates from specification (1). 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. Damage Business is relative business damage in a county, during a hurricane impact month or up to two months after the. Local 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. Damage Household is relative residential damage in a county during the impact month or up to two month after. Population 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. Fraction in 20-less Employee Firms/Fraction in 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. CountyGr4/CountyGr10 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.

	(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
Damage Businesses	-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)
Damage Businesses x Local 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)
Local 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)
Damage Households	-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)
Population 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)
Fraction in 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)
Fraction in 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 Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Ind x YearMonth FE			Yes							
CountyGr4 x Ind x YearMonth FE				Yes						
CountyGr10 x Ind x YearMonth FE					Yes	Yes	Yes	Yes	Yes	Yes
Sample	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	1b+ Hurricanes	1b- Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes
Damage Businesses at Local 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)
Damage Businesses at Local 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)
Damage Businesses at Local 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)

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

Table 5: Local Finance and Employment by Individual Industries

This table provides estimates from specification (1) using a different set of outcome variables compared to Table 4. Growth Establishments 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Growth			Employment Growth:			
VARIABLES	Establishments	Small Firms	Manufactoring	Trade, Transp, Util	Prof. Services	Hospitality	Other Serv.
Damage Businesses	-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)
Damage Businesses x Local 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)
Local 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)
Damage Households	-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)
Population 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)
Fraction in 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)
Fraction in 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 Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountyGr10 x Ind x YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes
Damage Businesses at Local 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)
Damage Businesses at Local 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)
Damage Businesses at Local 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)

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

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

This table examines how access to local finance is impacted by the characteristics of the local economy. The estimates are based on specification (2). High Productivity is an indicator for all counties with above median (state) lagged earnings in an industry. High 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. High 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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Dep Variable: Monthly Employment Growth				
Damage Businesses	-0.245***	-0.136***	-0.289***	-0.322***	-0.268***
	(0.0496)	(0.0445)	(0.0644)	(0.0763)	(0.0809)
Damage Businesses x Local Finance	0.686***	0.208	1.021***	0.789***	0.760***
	(0.241)	(0.125)	(0.238)	(0.266)	(0.166)
Damage Businesses x Local Finance x High Productivity		0.862**			0.839**
		(0.415)			(0.410)
Damage Businesses x Local Finance x High Industry Concentration			-0.466**		-0.539**
			(0.210)		(0.205)
Damage Businesses x Local Finance x High Geographic Concentration				-0.496**	-0.472**
				(0.226)	(0.196)
Damage Businesses x High Productivity		-0.251**			-0.219*
		(0.118)			(0.114)
Damage Businesses x High Industry Concentration			0.0164		0.00888
			(0.0677)		(0.0627)
Damage Businesses x High 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
Sample	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes	All Hurricanes
X= High Productivity/Industry Concentration/Geographic Concentr.					
Damage Businesses at Local 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)
Damage Businesses at Local 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)
Damage Businesses at Local 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)
Damage Businesses at Local Finance p25 and X=1		-0.387***	-0.273***	-0.169***	-0.487***
		(0.100)	(0.0554)	(0.0516)	(0.110)
Damage Businesses at Local Finance p50 and X=1		-0.237***	-0.195***	-0.128***	-0.263***
		(0.0699)	(0.0461)	(0.0434)	(0.0769)
Damage Businesses at Local Finance p75 and X=1		-0.00182	-0.0726	-0.0639	0.0891
		(0.0932)	(0.0805)	(0.0783)	(0.0938)

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

Table 7: 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 8: 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 7. Small/Big Community Banks are local lenders with more than 65% of deposits in one county and lagged assets below/above $300 mil. 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.

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
Damage Businesses x Small Community 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)
Damage Businesses x Big Community 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 Commitments	-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 Year x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes							
County Group 4 x Year 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

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

Table 9: 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
Damage Businesses	-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)
Damage Businesses x Local 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)
Local 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)
Damage Households	-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)
Population 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)
Fraction in 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)
Fraction in 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 Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountyGr10 x Ind x YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Damage Businesses at Local 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)
Damage Businesses at Local 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)
Damage Businesses at Local 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.

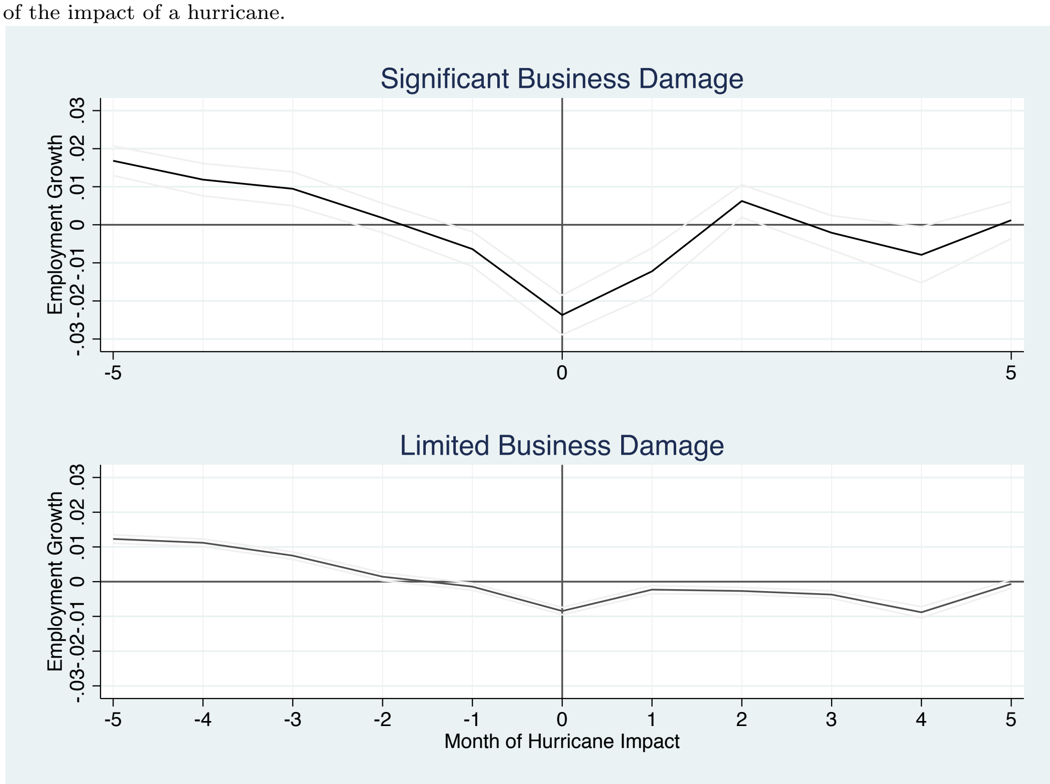
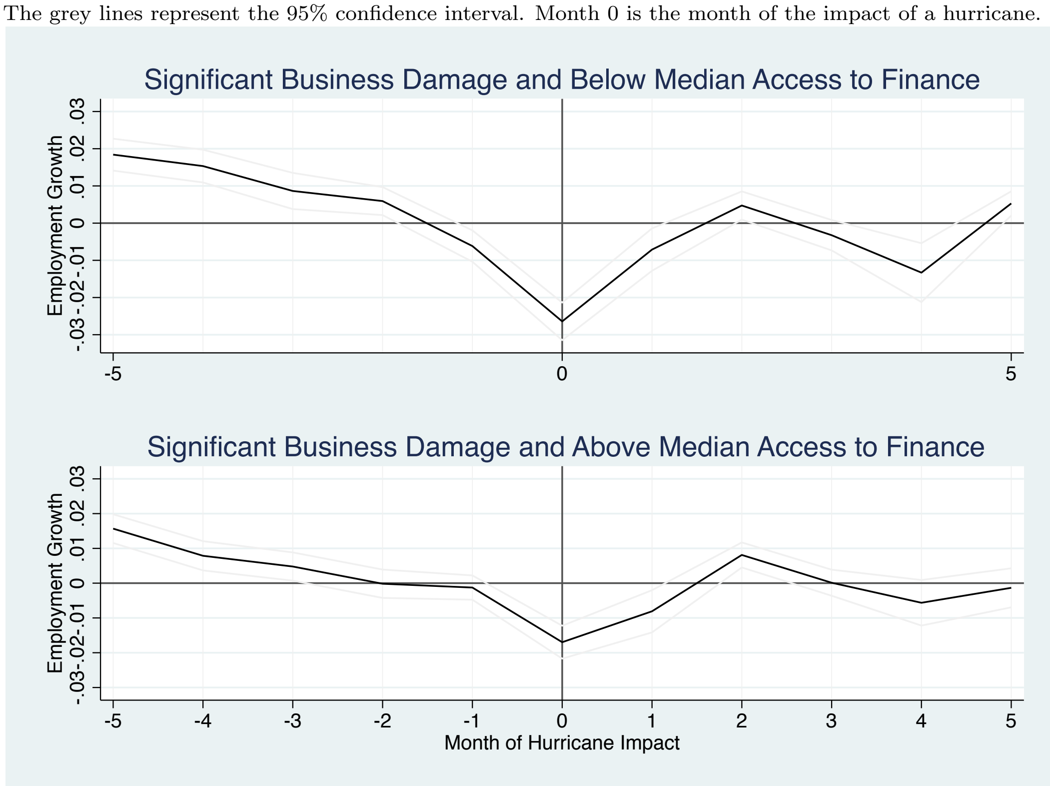


Figure 2: Access to Local Finance and Business Damage

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.



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