George Bailey Meets the Tempestates: How Local Finance Strengthens Economic Resilience Through Extreme Weather Events[†]

Vinzenz Peters, Maryann P. Feldman, W. Scott Langford, Mark Sanders*

03 December 2023

[Most recent draft here]

Abstract: The economic costs incurred by extreme weather events are substantial and increasing. In this study, we demonstrate how community banks – a type of financial institution with strong local ties and customer relationships – mitigate these costs. We use an event study model to demonstrate that US counties with higher community bank market shares experience fewer employment losses through extreme weather events. We then use bank-level analyses to demonstrate the mechanism – the small business credit supply. Community banks maintain their lending following extreme weather events, while other banks reduce it. These findings provide novel evidence on how local financial institutions strengthen economic resilience through extreme weather events. As policymakers develop strategies to mitigate the effects of extreme weather events, local finance may be a solution. For the financial system as a whole, this suggests a possible trade-off between efficiency and resilience.

Keywords: Environmental Economics, Economic Resilience, Financial Institutions
JEL Codes: G21, O12, R11, Q54

[†]We thank Jaap Bos, Meri Davlasheridze, Timothy Folta, Melanie Gall, Clemens Kool, Miles Parker, Stefan Straetmans, as well as seminar and conference participants at Arizona State University, Maastricht University, the Climate Finance, Risk and Uncertainty Modelling Conference at the Banque de France, the 3rd MORSE Conference in Maastricht, the Dutch Economists Conference in The Hague, and the Association for Public Policy & Management Conference in Atlanta for helpful comments and suggestions. This is a work in progress. Please do not circulate without author's permission.

*Peters: Maastricht University, E-Mail: vinzenz.peters@maastrichtuniversity.nl (corresponding author). Feldman: Arizona State University. E-Mail: maryann.feldman@asu.edu. Langford: Arizona State University. E-Mail: scott.langford@asu.edu. Sanders: Maastricht University. E-Mail: m.sanders@maastrichtuniversity.nl.

1. Introduction

The classic holiday film "*It's a Wonderful Life*" tells the story of *George Bailey*, a community banker, who dedicates himself to helping his community, ensuring households and businesses survive a bank run. The film is a reminder of the strong connections between community bankers and their customers, the value of relationships, and the real effect these can have on an economy. In this paper, we offer a new perspective on this story. Rather than a bank run, George faces the Roman goddesses of storms and extreme weather, *the Tempestates*, which ravage communities and are fueled by climate change. We demonstrate that George, the community banker, helps his community weather the threats posed by these tempestuous deities.

From an economic perspective, extreme weather events are a particular type of shock that causes property damage, business disruptions, and employment loss (Botzen *et al.*, 2019). Their costs are substantial and increasing (2003: $25.59 billion; 2020: $50.69 billion; author calculations)[1]. Climate change and the continued clustering of economic activity in regions frequently exposed to natural hazards are expected to further amplify this trend (Pielke *et al.*, 2008; Gall *et al.*, 2011; Estrada *et al.*, 2015; Hoeppe, 2016; IPCC, 2022). Insurance coverage and government assistance offset some of these costs, but significant gaps remain (Kousky, 2019; Collier *et al.*, 2020). Financial institutions may fill these gaps by providing credit, allowing firms to rebuild and continue operations effectively (McDermott *et al.*, 2014; Melecky and Raddatz, 2015). At the same time, financial institutions may differ in their *willingness* and *ability* to extend such recovery lending (Brei and Schclarek, 2015; Koetter *et al.*, 2020). Given the highly localized nature of extreme weather shocks (Botzen *et al.*, 2019), societies require financial systems that strengthen economic resilience at local levels as well as in the broader economy (Hallegatte, 2014; Lane, 2019).

In this study, we test the extent to which community banks, a type of financial institution with strong local ties and customer relationships, affect local economic resilience to extreme weather events. *Ex ante*, it is unclear if community banks strengthen or weaken economic resilience. When collateral is destroyed and uncertainty is high, community banks – as relationship lenders – can use soft information and local knowledge to continue lending in the aftermath of a

[1] To calculate the economic costs (country-year level), we use the mean property damage value (county-quarter level; per capita) in the analytic dataset. We multiply the mean property damage value by the number of quarters, persons per county and counties. 2003: $21.97 per person per county-quarter × 4 quarters × 105,898.40 persons / county × 2,750 counties = $25.59 billion. 2020: $37.26 per person per county-quarter × 4 quarters × 123,686.10 persons / county × 2,570 counties = $50.69 billion. Each property damage value has been adjusted to 2020 USD. Figure 1 presents trends in annual damages over time.

shock (Cole *et al.*, 2009; Berg and Schrader, 2012; Bolton *et al.*, 2016). Given the strategic importance of the local market to their business models, they may also have a strong self-interest in a strong local economic recovery (Berger *et al.*, 2017; Schüwer *et al.*, 2019). This can help firms retain employees, cushion adverse economic consequences, and spur economic recovery. Alternatively, community banks, which have fewer assets and smaller geographic diversification, may also experience weaker balance sheets through the destruction of physical assets and collateral. This may force them to reduce lending, thereby weakening local firms and exacerbating the economic consequences of extreme weather events.

To investigate this empirical question, we construct a county-quarter level panel dataset for the US in the period 2003-2020 and estimate the effect of the county-level community bank market share on employment growth through regular business cycle times and extreme weather events. To estimate a causal effect, we use an event study model, conditioning on unobservable state-quarter conditions, as well as a time-variant vector of socioeconomic, demographic, and banking characteristics. We find extreme weather events reduce employment growth for several quarters following an extreme weather event. The employment growth reductions are attenuated as the community bank market share increases.

Our estimates imply that an event that causes $100.00 in property damage, per capita, is expected to reduce employment growth by approximately one percent (79.27 workers) in the quarter of the event, when the community bank market share is 36.66 percent (the 2020 national average). In contrast, a county with a community bank market share of 54.91 percent (the 2003 national average) would be expected to see reductions of approximately 53.62 workers (0.7 percent).[2] Community banks thus have a substantial impact on economic resilience through extreme weather events.

Furthermore, we provide detailed insights into which banks contribute most to economic resilience along the bank size distribution. We observe an inverse U-shaped distributional effect – relatively large community banks (between $500 million and $1 billion in total assets) make the largest contributions to local economic resilience, compared to smaller community banks and larger, regionally, or nationally active banks. This is consistent with the notion that the smallest banks have larger balance sheet exposures that impede their capacity to maintain their lending relationships after severe events. Notably, a stronger presence of the top four largest banks of the

[2] The county-quarter sample mean employment is 48,370.19 workers.

US weakens local economic resilience – as the county-level market shares of these banks increase, employment losses through extreme weather events are exacerbated.

We expect community banks to contribute to local economic resilience through the credit supply, specifically small business lending. To investigate this, we use a bank-quarter-level panel dataset and an analogous event study model. We demonstrate that community banks lend at higher rates through extreme weather events. The average bank reduces its new small business lending by around 0.13 percentage points or 4 percent following an extreme weather event for each $100.00 in property damage per capita. Community banks, however, maintain their lending growth throughout the post-event period, ensuring their customers are able to access the necessary financial resources.

We conduct a series of robustness checks and alternative specifications to address identification concerns and strengthen the confidence that our results estimate a causal effect. These include Propensity Score Matching (PSM) to address concerns about selection bias, and placebo tests to ensure our results are not driven by secular trends in the main variables of interest. Our results remain consistent across specifications. In sum, our results demonstrate that community banks strengthen economic resilience through extreme weather events, and they achieve this by maintaining their small business credit supply. George Bailey meets the Tempestates head-on.

Our central contribution is demonstrating financial institutions with a local orientation strengthen local economic resilience to extreme weather events. While previous research demonstrates that relationship lending benefits borrowers and affected communities in the US through financial crises (Petach *et al.*, 2021; Langford and Feldman, 2022; Berger, Feldman, *et al.*, 2022) and public health crises (Li and Strahan, 2021; James *et al.*, 2021; Berger, Feldman, *et al.*, 2022), evidence on the case of extreme weather events is scarce. In a single-event study, Schüwer *et al.* (2019) suggest that affected counties with high shares of independent (not part of a bank holding company) and well-capitalized banks experienced higher economic growth after the landfall of the 2005 Hurricane Katrina. In this study, we provide more comprehensive and granular evidence on the role that locally oriented financial institutions, community banks, play in economic resilience across a range of extreme weather events of different types and intensities across the contiguous US.

We further contribute to the literature on credit supply reactions to natural hazard shocks. Extreme weather events adversely affect banks' balance sheets (e.g., Noth and Schüwer, 2023).

Despite this, US banks tend to satisfy spikes in credit demand (e.g., Cortés and Strahan, 2017; Bos *et al.*, 2022). Allen *et al.* (2022) show that community banks in particular satisfy the liquidity needs of their borrowers by increasing their loans in the aftermath of disasters. We extend this research by connecting bank-level lending activity to the real economy and by highlighting the credit supply to small businesses as a particularly important channel for the effect on employment.

Finally, in light of the recent trends of declining community bank market shares in the US (Berger *et al.*, 2017; Federal Reserve Board, 2018; FDIC, 2020), our results contribute to discussions around the real economic consequences of increasing market power of large banks and banking sector consolidation (Chen *et al.*, 2017; Nguyen 2019; Huber 2021). While larger banks may be considered more efficient in normal times (Berger *et al.*, 1999; Wheelock and Wilson, 2012; Hughes and Mester, 2013), our findings suggest the existence of a trade-off between efficiency and resilience. The consolidation of the banking industry may have enhanced efficiency, but it appears to weaken resilience to extreme weather events (and other shocks). In the face of increasingly frequent and destructive extreme weather shocks, this result bears important implications for financial regulators and policymakers engaged in discussions around climate change, economic resilience, and optimal banking market structure. Resilience may come at the cost of some inefficiency and lower profitability but as local economic resilience is a positive externality, we can argue that unregulated banking markets will undersupply relationship banking and propose that interventions are justified to address this market failure.

The remainder of this paper is organized as follows. In Section 2, we discuss prior research on the relationship between local finance and economic resilience. In Section 3, we outline the procedure we use to construct our datasets. In Section 4, we introduce our methodological approach and provide our main results. Here, we demonstrate community banks mitigate employment losses through extreme weather events. In Section 5, we investigate the underlying mechanism – we demonstrate that community banks continue to lend to small businesses through extreme weather events at higher rates relative to non-community banks. In Section 6, we provide conclusions, policy implications, and recommendations for future research.

2. Background

2.1 – Economic Resilience and Extreme Weather Events as Economic Shocks

Recent economic shocks, such as the Global Financial Crisis, and the COVID-19 pandemic, have sparked broad interest in the concept of economic resilience (Moser *et al.,* 2019). In general, regional economic resilience reflects a region's resistance (capacity to absorb), recoverability (rebound from), and adaptability (adapt to shocks) from shocks (Martin and Sunley, 2015; Martin *et al.,* 2016). In the context of extreme weather events, economic resilience can be understood as an economy's capacity to minimize welfare losses, conditional on the magnitude of the disaster (Hallegatte, 2014). Extreme weather events are exogenous to local economic activity and typically unpredictable in terms of their exact timing and location (Dell *et al.,* 2014). Through the destruction of physical assets and the disruption of business activity, extreme weather events have significant negative impacts on economic outcomes such as economic growth and employment. Previous research has empirically investigated a series of factors that influence a region's resilience to extreme weather events, which we use to inform our model construction (Klomp and Valckx, 2014; Lazzaroni and van Bergeijk, 2014; Botzen *et al.,* 2019). In the context of extreme weather events, the role of local financial conditions has previously remained understudied.

2.2 – Financial Institutions and Economic Resilience

Martin *et al.* (2016) argue that banks affect economic resilience through the credit supply. Empirical studies support this assertion through regular business cycle troughs (Bolton *et al.,* 2016), the Global Financial Crisis (Petach *et al.,* 2021; Langford and Feldman, 2022; Berger, Feldman, *et al.,* 2022), and the COVID Crisis (Levine *et al.,* 2020; Li and Strahan 2021; James *et al.,* 2021; Berger, Feldman, *et al.,* 2022). Through each of these events, local treatment intensity is difficult to observe, and often assumed to be consistent across regions - heterogeneous treatment effects are therefore a challenge for these studies. In this study, we use quarterly local property damages to observe extreme weather event intensity. This enables us to exploit variation over time and space to identify the mediating and moderating impact of local (pre)conditions on local resilience, strengthening the capacity to estimate causal effects.

As insurance and government aid typically only cover a fraction of the costs incurred through extreme weather events (Kousky, 2019; Collier *et al.,* 2020), their occurrence leads to increases in credit demand (Berg and Schrader, 2012; Cortés and Strahan, 2017; Ivanov *et al.,* 2022). By satisfying these spikes in credit demand, banks contribute to a faster recovery (McDermott *et al.*, 2014; Melecky and Raddatz, 2015). However, such events also pose unique challenges to banks. Through damage and destruction of assets and diminished borrower ability to service debt, banks experience weakened balance sheets, potentially restricting their capacity to extend new credit (e.g., Peters, 2023). Moreover, the destruction of collateral implies that existing information asymmetry problems are exacerbated (Berg and Schrader, 2012). Adequate access to credit is therefore a serious concern for firms affected by these shocks, especially for smaller and informationally opaque firms (Basker and Miranda, 2018; Collier *et al.*, 2020).

Relationship lending is a potential solution to such problems (e.g., Kysucky and Norden, 2016; Bolton *et al.*, 2016; Berger, Bouwman, *et al.*, 2022a, b). Relationship lending is typically associated with banks that are relatively small, geographically close to their borrowers, under local ownership, and oriented towards local businesses. In the US, community banks are typically regarded as relationship lenders (Kysucky and Norden, 2016; FDIC, 2020). In contrast, larger banks rely on transaction lending, which requires codified, "hard" information to make credit decisions in a standardized and efficiency-seeking way. This allows these banks to cut costs and expand their business across larger geographical areas (Berger and Udell, 2002; Berger *et al.*, 2005).

Relationship lenders rely on soft information, acquired over time through repeated personal interactions between lenders and borrowers, to inform credit decisions (Boot, 2000; Berger and Udell, 2002; Agarwal and Hauswald, 2010; Beck *et al.*, 2018). This soft information allows relationship banks to adapt their lending behavior based on information that is not available to transaction-based banks (Rajan, 1992; von Thadden, 1995; Cole *et al.*, 2009; Beck *et al.*, 2018).

Following extreme weather events, when collateral is compromised and economic uncertainty is high, relationship lending may be particularly useful. These events impact firms independent of their characteristics (e.g., size, industry, health). The severity of damage sustained does not provide information to the lender regarding the health of the firm and the trustworthiness of the borrower. As a result, creditworthiness as measured by hard information deteriorates. In these cases, employees of financial institutions, such as loan officers, with a strong knowledge of the local context and their borrowers may be better suited to assess risks and make credit decisions. Given their interdependence with the local economy, they may also have stronger incentives to ensure local firms survive and rebound, in order to preserve the bank's own customer base in the long term. Thus, community banks are likely better informed and more willing to extend recovery lending to affected businesses (Degryse and van Cayseele, 2000; Behr *et al.,* 2013; Koetter *et al.,* 2020). This would imply that community banks strengthen economic resilience.

Alternatively, one might argue that community banks weaken economic resilience. Given the localized nature of extreme weather events, a lack of financial and geographic diversification may increase the vulnerability of these banks. The adverse impacts of extreme weather shocks may be particularly hurtful to them, which may lead to lending reductions if the adverse effects on a small bank's balance sheet are substantial (Blickle *et al.,* 2022). In light of this, it ultimately remains an empirical question as to which type of banking is most conducive to economic resilience in the face of extreme weather shocks.

2.3 – How Financial Institutions Moderate the Effects of Extreme Weather Events

Existing empirical evidence suggests that weather-related disasters weaken the financial health of banks active in affected regions (Apergis, 2022; Do *et al.,* 2022; Walker *et al.,* 2022; Noth and Schüwer, 2023). Noth and Schüwer (2023), for instance, show that damages from weather shocks induce higher non-performing asset ratios, higher probabilities of default, and diminished profitability in the two years after a shock. The empirical evidence on heterogeneous effects across bank size is ambiguous (Blickle *et al.,* 2022, Walker *et al.,* 2022, Noth and Schüwer, 2023). For all types of banks, better pre-shock capitalization is found to mitigate the negative impacts on the financial stability of the exposed institutions (see Peters (2023) for a comprehensive discussion). We therefore condition our results on a series of bank health control variables.

The empirical evidence of studies focusing on the US further indicates that credit demand rises following extreme weather shocks (e.g., Brown *et al.,* 2021; Ivanov *et al.,* 2022), while the measured creditworthiness of borrowers is impaired (Gallagher and Hartley, 2017; Ratcliffe *et al.,* 2020). Credit demand spikes are generally met by increased credit supply of banks (Cortés and Strahan, 2017; Bos, *et al.,* 2022), but bank characteristics create significant heterogeneity in the extent of these lending reactions. For example, financial institutions with better capital buffers provide more loans in the aftermath of a shock (Schüwer *et al.*, 2019), as do institutions in less competitive banking markets (Duqi *et al.,* 2021). Each of these studies associates increased lending with better recovery outcomes for affected economies. Furthermore, Duqi *et al.* (2021) indicate that a significant share of post-disaster lending occurs in the form of disaster loans which banks intermediate on behalf of the Small Business Administration (SBA). These loans are guaranteed by the federal government but originated by banks. We also use this information to guide the selection of our control variables.

The specific link between relationship-oriented banks and extreme weather events in the US has received little attention. Cortés (2014) as well as Allen *et al.* (2022) report that local lenders respond to natural hazard shocks by increasing their loan supply in affected regions. Schüwer *et al.* (2019) find similar results in the aftermath of the 2005 Hurricane Katrina for independent banks (banks that are not part of a holding company). Moreover, Cortés (2014), as well as Schüwer *et al.* (2019), find locally oriented banks partially mitigate the economic costs of these events. Cortés (2014) provides suggestive evidence that local lenders with highly concentrated deposit shares might also mitigate the employment losses of specific types of disasters.

In contrast, Blickle *et al.* (2022) find no significant changes in local bank lending after weather disasters. Petkov (2022) suggests that a lack of geographic diversification leads local lenders to experience higher loan portfolio losses, depressing their ability to extend recovery funding, which in turn exacerbates employment contractions after highly damaging disasters. Each study finds diversified banks, as defined by operating in multiple markets, increase their lending after natural hazard shocks.

We expand upon these studies in several ways. First, we provide comprehensive evidence on how locally oriented banks strengthen economic resilience to extreme weather events. We then provide evidence for the mechanism through which banks achieve this – the small business credit supply. Also, whereas prior studies presented correlational evidence, we use an event study design to identify the causal link from banking market structure to economic resilience. Finally, we assess the heterogeneity of our result across the bank size distribution to provide further insights into which types of banks are most conducive to local economic resilience in the face of extreme weather shocks.

3. Data

3.1 – Data Sources

We use two datasets in this study. To estimate our main effect, we use a county-quarter-level dataset. To investigate the underlying mechanism, we use a bank-quarter-level dataset. Using the county-quarter level dataset, we estimate the effect of the community bank market share on economic resilience. To observe economic resilience, we use employment growth, constructed using employment data obtained from Quarterly Workforce Indicators (QWI). As our primary treatment variable, we use the per capita value of property damage from the Spatial Hazards Events and Losses Database for the United States (SHELDUS), which is maintained and provided by the Center for Emergency Management and Homeland Security of Arizona State University (CEMHS, 2023). As our focus lies on extreme weather events, we specifically consider weather-related hazards registered in SHELDUS, including different types of floods and storms, droughts, wildfires, and extreme winter weather (see Table 1 for a complete list). We use the community bank market share to proxy for the presence of community banks. We construct the community bank market share variable using bank branch location, branch deposits, and bank asset information collected from the FDIC Summary of Deposits. In the primary specification, we classify banks as community banks using the bank asset values collected from the FDIC Summary of Deposits, as it is commonly practiced in the literature (Carter and McNulty, 2003; Berger and Black, 2011; Levine *et al.*, 2020; Petach *et al.*, 2021). In an alternative specification, we use the community bank definition constructed by the FDIC, which takes into account additional bank characteristics, such as geographic footprint and business activities (FDIC 2020, 2023).

In the bank-quarter-level dataset, we investigate the underlying mechanism. We estimate the effect of the community bank status on small business lending through an extreme weather event. In this analysis, we use small business lending growth to observe lending activity, as obtained via the FFIEC Regulatory Call Reports. We construct the community bank status and extreme weather event variables using sources and definitions consistent with the county-level dataset.

Omitted variable bias is one of our chief identification concerns here – counties that have higher community bank market shares and stronger economic resilience may be unique along other dimensions. Similarly, at the bank-level, community banks may have branch networks spread across counties with unique characteristics. For example, bank health may be an intervening influence (e.g., Chodorow-Reich, 2014; Kiser *et al.*, 2015; Peters, 2023). To mitigate these concerns, we condition on a consistent set of local characteristics in each analysis, including a vector of time-variant socio-economic, demographic and bank health control variables (described in table 1).

First, we obtain a series of socio-economic and demographic characteristics from the US Census Bureau. We then obtain industrial composition data from the Quarterly Census of Employment and Wages (QCEW), as well as the Housing Price Index from the Federal Housing Finance

Agency (FHFA). These variables are collected at the county-level. For bank-level analyses, we use the branch network to construct deposit-weighted bank-level variables that represent the characteristics of the geographic footprint of the bank.

Finally, we obtain bank health control variables. We collect bank-level financial data for each commercial bank in the US from the FFIEC Regulatory Call Reports. For county-level analyses, we use the branch network to construct deposit-weighted county-level variables that represent the characteristics of the banks within the county. We limit our sample to commercial banks with non-missing values for the key variables (total assets, common equity). Each financial variable has been adjusted using a GDP deflator to 2020 real USD.

The datasets are constructed for a sample running from 2003 to 2020. The county-quarter level dataset used in our preferred specification contains 137,372 observations over 2,750 counties (87.5 % of US counties by number; 96.7 % by population). The bank-quarter level dataset contains 158,017 observations over 5,656 banks (91.2 % by number). Tables 2A-B and 3A-B present descriptive statistics for the county- and bank-level variables used in the analyses.

3.2 – Trends in Extreme Weather Event Severity and Community Bank Market Shares in the US

To provide context for our analyses and further motivate this study, we first examine trends in extreme weather event severity and community bank market share. Prior research demonstrates that the US is highly exposed to natural hazards and that both the number of disastrous events (Boustan *et al.*, 2020) and the associated costs have increased in recent decades (Pielke *et al.*, 2008; Gall *et al.*, 2011; Estrada *et al.*, 2015). Concurrently, branch deregulation (Janicki and Prescott, 2006), technological innovation, and post-Global Financial Crisis consolidation have concentrated the banking industry (Berger *et al.*, 1999; DeYoung *et al.*, 2004; Federal Reserve Board, 2018; FDIC, 2020).

We examine these trends in our dataset. In Figure 1, the mean annual (GDP deflated) property damage is shown as a solid red line. Over the period of interest, 2003-2020, the year with the highest recorded extreme weather damage was 2005 ($166.49 per capita). Notably, three out of the four most damaging years lie towards the end of our panel (2017: $48.83, 2018: $54.99, 2020: $37.26). Over the same period, the mean community bank share (dashed blue line) decreased by approximately 18 percentage points (2003: 54.91%; 2020: 36.66%). Overall, extreme weather events are becoming more costly, while community banks are becoming less prevalent.

These phenomena are also geographic in nature – extreme weather and community banks are dispersed unevenly across space. To examine this, we construct a series of maps, which provide the mean community bank share (Figure 2A), change in community bank share (Figure 2B), and mean extreme weather event property damage (Figure 2C). Figure 2A demonstrates community banks are distributed across the US, with the highest market shares observed in the Great Plains, Mid-West and Deep South. Consistent with our previous analysis, Figure 2B demonstrates the market shares of community banks have declined significantly across the US, with interspersed pockets where community banks have gained ground. Finally, Figure 2C demonstrates extreme weather events are distributed quite evenly across the US, with some concentration in the expected areas (e.g., Tornado Alley, Gulf Coast).

Notably, Figure 2B demonstrates there is significant heterogeneity in the change in community bank market share across space. To identify the factors that drive the community bank market share across space, we completed a series of regressions using the county-level dataset (see Table A1). The dependent variable is the community bank market share. Across specifications, we include socio-economic and demographic characteristics, as well as year-quarter fixed effects. In models 2 and 4, we incorporate bank health characteristics. To take into account time-invariant county-level characteristics, in Models 3 and 4, we also include county fixed effects. These regressions indicate regions with higher small-medium enterprise employment share, as well as lower educational attainment, foreign born residents and housing price index experience higher community bank market shares. Notably, several of the bank health characteristics appear to drive the community bank market share, and inclusion of these characteristics significantly strengthens the predictive power of this model. We thus conclude that our main specification, as discussed in section 4.1, adequately accounts for the factors that drive the changes in community bank market shares across space. Moreover, we present additional robustness checks addressing this aspect in section 4.5.

4. Main Results - The Effect of Community Banks on Economic Resilience

4.1 – Empirical Strategy

The physical impacts of extreme weather events are typically localized (Botzen *et al.*, 2019) and can be short-lived (Strobl, 2011). We thus use the county (i) – quarter (t) as our unit of analysis. We estimate:

$$\Delta\, Employment_{it} = \beta_1 \cdot Community\ Bank\ Share_{it} +$$
$$\beta_l^1 \cdot Event\ Severity_{it+l} + \beta_l^2 \cdot Community\ Bank\ Share_{it} \cdot Event\ Severity_{it+l} +$$
$$\gamma\ \cdot\ U_{it} + State - Year - Quarter\ FE_{st} + \varepsilon_{it}$$
$$l = -10 \ldots + 10$$

The dependent variable ($\Delta\, Employment_{it}$) is the quarter-over-quarter percent change in employment. There are three key independent variables: $Community\ Bank\ Share_{it}$, defined as the proportion of all deposits held by community banks (banks with less than \$1 billion in assets in the preferred specification); $Event\ Severity_{it+l}$, defined as the per capita property damage value in dollar (at 2020 prices); and the interaction term, $Community\ Bank\ Share_{it} \cdot Disaster\ Severity_{it+l}$. $Event\ Severity$ and the interaction term are constructed as a series of leads and lags. The $Event\ Severity$ coefficient estimates (β_l^1) capture the average economic impacts of an event with given severity (for a zero community bank market share), while the interaction terms (β_l^2) capture the average effect of having more community banks and relationship lending on the counties' ability to withstand and recover from extreme weather shocks. To condition our results on time-variant local conditions, we include state-year-quarter fixed effects.

This model estimates two key effects: (1) the effect of extreme weather property damage on employment growth, and (2) the interactive effect of community bank market share and extreme weather event property damage on employment growth. Identification rests on the assumption that treatment with extreme weather damage is exogenous to employment growth and orthogonal to the error term ε_{it}. Extreme weather events are unpredictable in terms of their timing, intensity, and location, relative to the regional level of long-term disaster risk (e.g., Dell *et al.*, 2014; Duqi *et al.*, 2021; Noth and Schüwer, 2023). Their occurrence and the following damage can thus be considered independent of the rate of local employment growth, ensuring the β_l^1 are unbiased. Furthermore, prior literature shows that estimates of the coefficient on the interaction terms, β_l^2, are unbiased and consistent under two additional conditions (Nizalova and Murtazashvili, 2016; Bun and Harrison, 2019; Duqi *et al.*, 2021).

In our case, this requires (1) extreme weather damage is independent of the community bank market share (i.e., $E(Event\ Severity_{it+l}, Community\ Bank\ Share_{it} = 0)$), and (2) extreme weather damage is independent of the error term conditional on community bank market shares (i.e., $E(Event\ Severity_{it+l}, \varepsilon_{it}|Community\ Bank\ Share_{it} = 0)$). In other words, in line with previous literature, we rely on the quasi-experimental nature of extreme weather events, conditional on time- and location-specific effects (e.g., Dell *et al.*, 2014; Duqi *et al.*, 2021; Noth and Schüwer, 2023).

We also include a battery of time-variant socio-economic and demographic control variables, which are selected based on previous literature in order to account for determinants of local economic resilience other than the local banking structure (Noy and Yonson, 2018). These include the population shares of Female, Working Age (25-64), Bachelor's Degree, African-American, Asian, Other, Hispanic, and Foreign Born, Population Density, the Non-Disaster Related Death Rate, the Median Household Income (Log), and the Federal Housing Finance Agency's Housing Price Index. Given the importance of insurance for mitigating the adverse impacts of extreme weather events (e.g., Kousky, 2019), we also include the Number of Flood Insurance Policies (per capita). Furthermore, the impacts of extreme weather events differ across industrial sectors and the characteristics of local businesses (Xiao and Drucker, 2014; Basker and Miranda, 2018), while industrial composition itself is an important factor in economic resilience (Martin *et al.,* 2016). We therefore include control variables that characterize the local industrial and business structure (employment shares of Manufacturing, Entertainment, Hotels and Food, Public Administration, as well as Small and Medium-Sized Enterprise).

We further include bank-level control variables to ensure our main results are not driven by, for instance, differences in bank health or regulatory requirements across banks, as discussed in section 2.3. These are the Herfindahl–Hirschman Index, Capital Adequacy, Asset Quality, Management Quality, Earnings, Liquidity, Sensitivity to Market Risk, Bank Age, Bank Holding Company Ownership, Foreign Ownership, OCC Regulation, FDIC Regulation, Federal Reserve Regulation, Fee to Income Ratio, Income Diversity, Deposits Ratio, Total Loans to Assets Ratio and Deposits in Metropolitan Regions. Complete variable definitions are provided in Table 1. Tables 2A and 2B provide summary statistics.

4.2 – The Effect of Community Bank Market Share on Employment

Using the model outlined in section 4.1, we test if extreme weather events cause employment losses, and if higher market shares of community banks mitigate these employment losses. These results are presented in Figure 3. Figure 3A demonstrates extreme weather events cause immediate and persistent employment losses, extending for about one year (see Table A1 for full regression results; Model 1 is the preferred specification). These results are consistent with prior studies, which demonstrate that extreme weather events reduce local economic activity in US counties (e.g., Strobl, 2011; Boustan *et al.*, 2020). Treatment variable leads show no significant patterns, indicating the absence of any pre-trends, as we would expect given the inherent unpredictability of extreme weather events (and as discussed in section 4.1). This strengthens our confidence that our model estimates a causal effect.

Figure 3B shows that the presence of community banks mitigates these employment losses, and these effects extend beyond the effects of the event. Our calculations indicate that an extreme weather event causing $100.00 per capita property damage would lead to a decrease in employment growth in an average county with a community bank market share of 36.66 percent (the 2020 national average) by 79.27 workers, representing approximately 1 percent during the quarter of the event. In contrast, a county with a community bank share of 54.91 percent (the 2003 national average) would experience a reduction of approximately 53.62 workers (0.7 percent). Put differently, a one-standard-deviation increase in per capita property damage (sample mean: $27.20, SD: $1,564.24) decreases the quarter-over-quarter employment growth (sample mean: 0.16%, SD: 1.00%) on average by around 0.0194 percentage points in the quarter of the event, with negative effects lasting up to the third quarter after the shock. A one-standard-deviation increase in the community bank market share (sample mean: 47.49%, SD: 34.55%) mitigates these negative employment consequences by around 0.0127 percentage points in the quarter of the event, with positive effects lasting up to 6 quarters after the event. These findings underscore the substantial and statistically significant positive influence of community banks on employment and local economic resilience during extreme weather events.

4.3 – Effects Along the Bank Size Distribution

Our primary specifications define community banks as financial institutions with fewer than $1 billion in assets. This threshold is consistent with prior research (Carter and McNulty, 2003; Berger and Black, 2011; Levine *et al.*, 2020; Petach *et al.*, 2021; Langford and Feldman, 2022). We also expect differential effects to be observed along the size distribution. To examine this, we estimate our main model using different bank size thresholds. We have three expectations here: (1) regions with higher market shares of larger banks, which typically engage in transaction lending, will be less resilient, (2) regions with higher market shares of smaller banks, which engage in relationship lending, will be more resilient, (3) regions with higher market shares of the smallest banks, which may have inadequate resources to maintain lending after large shocks, will be less resilient. In sum, we expect to observe an inverse U-shaped curve, where banks at extremely high and low asset values weaken resilience, and around an optimal asset value, banks strengthen resilience.

First, we estimate the effect of banks across the size distribution on economic resilience. We construct a series of market share variables, and use the model outlined previously, to estimate the effect of each bank size group on economic resilience (see Figure A1). To capture the effect in one coefficient, we choose a conservative approach and use the combined fourth and fifth lag of property damage.[3] We further define the relevant treatment groups "from two sides" to ensure consistent control groups. We first estimate three models using the combined deposit market shares of banks *smaller* than \$100 million, \$500 million, \$1 billion (our baseline community bank definition), and \$5 billion in total assets, respectively. Banks with market shares larger than these thresholds form the control groups. Then, we consider the combined market shares of banks *larger* than the following thresholds: \$5 billion, \$10 billion, \$50 billion, \$100 billion, \$500 billion, and \$1 trillion in total assets. In these cases, banks below the thresholds are the respective control groups.[4]

Consistent with expectations, we find the market shares of banks below \$1 billion to exert significantly positive effects on post-event employment growth. The effects for the smallest banks (< 500 million) are positive but insignificant. These results indicate that smaller (< 1 billion) banks strengthen economic resilience, compared to larger banks (> 1 billion), but the effect is driven by the small banks with > 100 million in assets. As we increase the bank size thresholds and consider the market shares of increasingly larger banks, the estimated coefficients become increasingly negative, but also more imprecise.

Second, we specifically estimate the effect of the market share of the top four largest banks on post-shock employment growth. These nationally active banks have expanded rapidly in recent decades (FDIC, 2020), driven by interstate deregulation (Rice and Strahan, 2010; Krishnan *et al.*, 2015) and technological advances (DeYoung *et al.,* 2004). However, their effect on local economic resilience is unclear, *a priori*. These banks engage in transaction lending, rather than relationship

[3] This is consistent with the results on bank lending responses to extreme weather damage, which we show and discuss in section 5.2. We test different lags on this exercise and it does not alter results significantly.
[4] In this way, we ensure we have coherent control groups in all models, making it easier to interpret the estimated coefficients.

lending, and rely on hard, codified information and collateral to make lending decisions. Given that collateral is damaged or destroyed and that credit scores deteriorate after extreme weather events (Ratcliffe *et al.*, 2020), we expect these national banks to either weaken economic resilience or have a null effect. Alternatively, these banks, whose branch networks are spread across space, may benefit from better diversification and risk-sharing across space and have a greater capacity to shift resources to regions experiencing an expansion in credit demand.

To test this, we construct a variable that captures the market share of the top four national banks for each quarter. Using the same model as outlined in section 4.1, we estimate the effect of these banks on economic resilience (see Figure A2). The results indicate that, as the market share of the top four banks increases, post-shock employment growth is weakened. In sum, our results show that smaller and arguably more locally embedded banks strengthen economic resilience, while the largest banks reduce local economic resilience to extreme weather events.

4.4 – Differential Effects by Disaster Type, Firm Size and Age

Our main results demonstrate community banks mitigate employment losses through extreme weather events. To further qualify our results, we identify the types of firms through which the effect of community bank market shares on employment growth works. In principle, longer-lasting relationships allow lenders to obtain more and better private information about borrowers (Kysucky and Norden, 2016). Older firms with longer banking relationships should therefore benefit more from a greater community bank presence. In contrast to this, Cortés (2014) suggests that young or small firms benefit the most from local lenders in the aftermath of natural disasters. We conduct a series of regressions using alternative dependent variables that capture employment growth across firm size and age (see Table A3). Our results show that the benefits of community bank presence are stronger for older and larger firms, underscoring the notion that it's long-term, established relationships between borrowers and banks that strengthen economic resilience.

Furthermore, previous literature suggests that different types of extreme weather events may have different effects on local economies (e.g., Botzen *et al.*, 2019; Peters *et al.*, 2023). For example, the economy of a region that experiences a hurricane may be impacted differently than the economy of a region that experiences a flood, while experiencing the same magnitude of property damage. To examine this, we conduct a series of regressions using the property damage of each event type separately (see Table A4). Our results remain significant for hurricanes, and turn insignificant for several other types of events. Other types of events have fewer observations, suggesting this is driven by lower statistical power.

4.5 – Alternative Specifications and Robustness Checks

We construct a series of alternative specifications and regressions to assess the robustness of our results. First, the concern arises that our control variables are affected by extreme weather events, potentially biasing the results of our event study models through "bad controls" (Angrist and Pischke, 2009; Dell *et al.*, 2014; Acevedo *et al.*, 2020). To mitigate this concern, we construct specifications without control variables and with only county control variables (Table A2; Models 2 and 3). The results are consistent across specifications.

Second, while SHELDUS is considered the most reliable and comprehensive data source for disaster impacts in the US, it has some limitations (Gall *et al.*, 2009). One such limitation is related to its averaging of disaster losses from an event across counties, which, for a single incident, results in equal total damage amounts across affected communities. However, wherever exact information on the location of fatalities is available, SHELDUS will use this to better represent patterns of event severity (CEMHS, 2023). To mitigate concerns regarding the construction of the property damage variable, we construct specifications that measure extreme weather event intensity with fatalities (Table A2; Model 4). The results are consistent in this specification.

Third, the value of property damage will likely vary with the local level of income in an affected county. While this should largely be accounted for through the inclusion of median household income levels and fixed effects in our preferred specification, we estimate an alternative model that uses GDP to scale the county-level property damage variable (Table A2; Model 5). The results are consistent in this specification.

Fourth, selection bias may be another concern. Not only may counties that experience extreme weather events or counties that have community banks be different from those that do not, it may also be that changes in community bank market shares correlate with a changing probability of being treated with extreme weather events. To mitigate concerns around this, we construct three specifications. First, counties that experience extreme weather events may differ from those that do not. To address this concern, we first limit the sample to those counties that experienced extreme weather event property damage (Table A2; Model 6). Second, counties with higher community bank market shares may differ from those with lower community bank market shares. To address this concern, we use a Propensity Score Matching (PSM) approach. We use socio-economic and demographic variables to estimate the probability that counties have community banks and limit the sample to those with similar probabilities (Model 7). Finally, we use a combination of these specifications, and limit our sample to those counties that experience extreme weather events, and counties with similar probabilities of having community banks (Model 8). The sign and magnitude of each key coefficient remain consistent across specifications.

Fifth, we check whether our results hold when we use the FDIC's definition of community banks instead of the simpler asset-based definition (< $1 billion in total assets). The FDIC definition takes into account additional bank characteristics, such as geographic footprint and business activities (FDIC 2020, 2023). Our main result remains unchanged (see Figure A4).

Lastly, if areas that experience extreme weather events are experiencing long-term economic decline, or if areas with higher community bank market shares are experiencing long-term economic growth, then our results may be artifacts of these trends. Alternatively phrased, secular trends in employment growth and community bank market shares may drive the observed results. If this were the case, we would expect to observe significant pre-trends in employment growth in the main results prior to the extreme weather shock – we do not observe this. To strengthen our confidence in this, we conduct a placebo test, where property damage values are randomly redistributed (see Figure A5). The coefficient estimates are consistently zero across leads and lags. This provides evidence consistent with secular trends in employment growth and community bank market share not driving the observed result.

5. Mechanisms: The Effect of Community Bank Status on Small Business Lending

5.1 – Empirical Strategy

The results in section 4 demonstrate extreme weather events cause employment growth reductions, and community banks mitigate these effects. We expect that the main mechanism through which these banks achieve this is the small business credit supply, filling financing gaps that insurance and government support do not cover. As discussed in Section 2, relatively small, regional businesses are typically the most vulnerable to extreme weather events. Furthermore, the destruction of collateral value and increases in information asymmetries can complicate banks' credit decisions. In such situations, banks may show different abilities and willingness to extend recovery lending, depending on their lending technology, capitalization, and business models. As financial institutions with strong relations to the local business community and pronounced self-interests to support local economic activity, community banks are likely more able and willing to extend recovery lending to affected businesses in the aftermath of a shock. Therefore, we investigate the response of banks' small business lending activities as a means through which they enhance the resilience of local employment growth. In this model, the unit of analysis is the bank (i) – quarter (t). We estimate:

$$\Delta\, Small\ Business\ Loans_{it} = \beta_1 \cdot Community\ Bank_{it} +$$
$$\beta_l^1 \cdot Event\ Severity_{it+l} + \beta_l^2 \cdot Community\ Bank_{it} \cdot Event\ Severity_{it+l} +$$
$$\gamma \ \cdot \ U_{it} + Year - Quarter\ FE_{st} + \varepsilon_{it}$$
$$l = \ -10 \ldots + 10$$

The dependent variable ($\Delta\, Small\ Business\ Loans_{it}$) is the quarter-over-quarter percent change in small business loan value. There are three key independent variables: $Community\ Bank_{it}$, defined as an indicator variable equal to one if the bank is classified as a community bank (banks with less than \$1 billion in assets) and zero otherwise; $Event\ Severity_{it+l}$, defined as the per capita property damage value in USD (inflation adjusted to 2020 prices); and the interaction term, $Community\ Bank_{it} \cdot Event\ Severity_{it+l}$. The latter two are constructed as series of leads and lags. For county-level variables (e.g., $Event\ Severity_{it+l}$), we aggregate the county-level variables to the bank-level using the branch network. For example, in this model, the $Event\ Severity_{it+l}$ variable represents the deposit-weighted mean property damage experienced by the counties in the branch network of the bank.

Identification rests on the exogeneity of the timing, intensity, and location of extreme weather events (see discussion in Section 4.1). For consistency, we select the same set of control variables as in the preferred specification in Section 4.1. The set of controls accounts comprehensively for local banking market characteristics as well as bank-level characteristics that determine the small business lending activities of banks. Importantly, and as discussed in Section 2.3, the set of control variables ensures in particular that our results are not driven by differences in bank health or regulation. Complete variable definitions are provided in Table 1B. Tables 3A and 3B provide summary statistics.

5.2 – The Effect of Community Bank Status on Small Business Lending

Similar to the county-level analysis, we use an event study model to test if extreme weather events cause declines in small business lending, and if community banks reduce their lending less than non-community banks after extreme weather events. These results are presented in Figure 4 (see Table A6, Model 1 for full results). Figure 4A demonstrates small business lending tightening associated with extreme weather events is significant, though delayed. Extreme weather events cause small business lending tightening in the fourth and fifth quarters following the event. For each $100.00 property damage (per capita), small business lending growth is expected to be reduced by approximately 0.13 percentage points or around 4 percent of the mean small business lending growth in each of these quarters.[5] Figure 4B shows that community banks do not tighten lending – non-community banks drive the observed reduction in lending. The positive coefficients on the interaction term, $Community\ Bank_{it} \cdot Event\ Severity_{it+l}$, of the fourth and fifth quarter after the events imply that community banks maintain their lending at pre-shock growth rates throughout the post-event period. These results point towards the small business credit supply as a mechanism through which community banks mitigate the employment losses associated with extreme weather events.

5.4 – Alternative Specifications and Robustness Checks

Similar to the county-level analyses, we construct a series of alternative model specifications and tests to assess the robustness of our results. We estimate a series of alternative specifications that vary the included sets of control variables and the choice of fixed effects to mitigate concerns around control variable selection (see Table A6, Models 2-6). To address concerns around independent variable construction, we use fatalities and property damage per GDP instead of property damage per capita (see Table A7, Models 1-2). We further construct three specification to alleviate concerns around selection (see Table A7, Models 3-5). The first specification limits the sample to those banks that experienced extreme weather event property damage (Model 3). The second specification uses the PSM technique and socio-economic and demographic variables to estimate the probability banks are community banks, and limits the sample to those with similar probabilities (Model 4). Then, we use a combination of each specification to limit the sample to

[5] The mean coefficient estimate ([-0.0013164 - 0.0013426] / 2 = -0.001330) represents the quarter-over-quarter percentage point change in small business lending per dollar value of property damage over this time period. We multiply this coefficient by $100 to take into account event magnitudes.

those banks that experience extreme weather events, and have similar probabilities of being community banks (Model 5). The results remain consistent across all specifications.

Finally, we conduct a placebo test where property damage values were randomly redistributed to mitigate concerns regarding secular trends driving the observed results (see Figure A6). These coefficients are consistently zero, strengthening our confidence in the main specification.

6. Discussion and Conclusion

This paper shows that small, relationship-oriented banks such as community banks mitigate the employment consequences of extreme weather events in the US. The main mechanism for this effect is the credit supply, in particular small business lending. Notably, banks with asset sizes between $500 million and $1 billion appear to be the most conducive to local economic resilience, while the largest banks do not contribute to local economic resilience. Firms with a longer track record seem to benefit the most from community bank presence. Together, these results strongly suggest that local relationship-oriented financial institutions strengthen economic resilience through extreme weather events.

Prior studies provided evidence that community banks strengthen economic resilience to financial and public health crises in the US (Levine *et al.,* 2020; Li and Strahan, 2021; James *et al.*, 2021; Petach *et al.,* 2021; Langford and Feldman, 2022). Our study extends these results to extreme weather events. Schüwer *et al.* (2019) use a single event, Hurricane Katrina, to examine the effect of local finance on local economic development following a catastrophic shock. Our study extends this evidence across a much broader range of extreme weather events of different types and intensities. Moreover, we demonstrate that community banks achieve these benefits by maintaining their credit supply, which is broadly consistent with prior studies (Schüwer *et al.*, 2019; Allen *et al.*, 2022), though not all (Blickle *et al.*, 2022). In contrast to these previous studies, which examine overall lending or mortgage loans, we show the particular response of community banks' small business lending, which is key to maintaining jobs and directly caters to the needs of the most vulnerable firms (Davlasheridze and Geylani, 2017; Basker and Miranda, 2018). Finally, extant research points to relationship lending as a powerful mechanism for overcoming credit supply issues through crises (Kysucki and Norden, 2016). Our finding that older, more established firms drive the observed result is consistent with this explanation. In sum, our results are consistent with existing research and point to an additional circumstance in which relationship lending proves useful – extreme weather events.

Unpacking the underlying heterogeneity in our results across the bank size distribution, we find that banks above \$500 million but below \$1 billion in assets show the strongest effect on economic resilience. These banks are more likely to rely on relationship lending. At the same time, they are big enough not to be too vulnerable to the shock themselves. The smallest and most localized banks (< \$500 million in total assets), while relationship-oriented, likely lack the risk-sharing capacities and resources to significantly enhance economic resilience, especially after more severe shocks. Thus, we do not find their presence to have significant positive effects on resilience.

Our findings present a new dimension in the debate about the role of large banks (Berger *et al.*, 2005; Chen *et al.*, 2017; Huber, 2021) and increasingly big financial sectors more generally (e.g., Law and Singh, 2014; Laeven *et al.*, 2014; Arcand *et al.*, 2015; Ioannou and Wójcik, 2021). Large, transaction-oriented banks are considered more efficient and profitable in normal times (e.g., Berger *et al.*, 1999). However, we find evidence that national banks, which have large, diverse branch networks and more resources, weaken local economic resilience. As community banks are competed out of their local markets by such national banks, our results point to a potential trade-off between efficiency and resilience. In streamlining the banking sector towards more transaction-oriented, larger banks, we sacrifice the resilience of communities which require access to local finance when faced with shocks. In times of frequent economic and non-economic shocks, this raises the question of what an optimal structure of the financial system would look like. Financial regulation and supervision should aim to balance efficiency and resilience. Future research is needed to make these trade-offs.

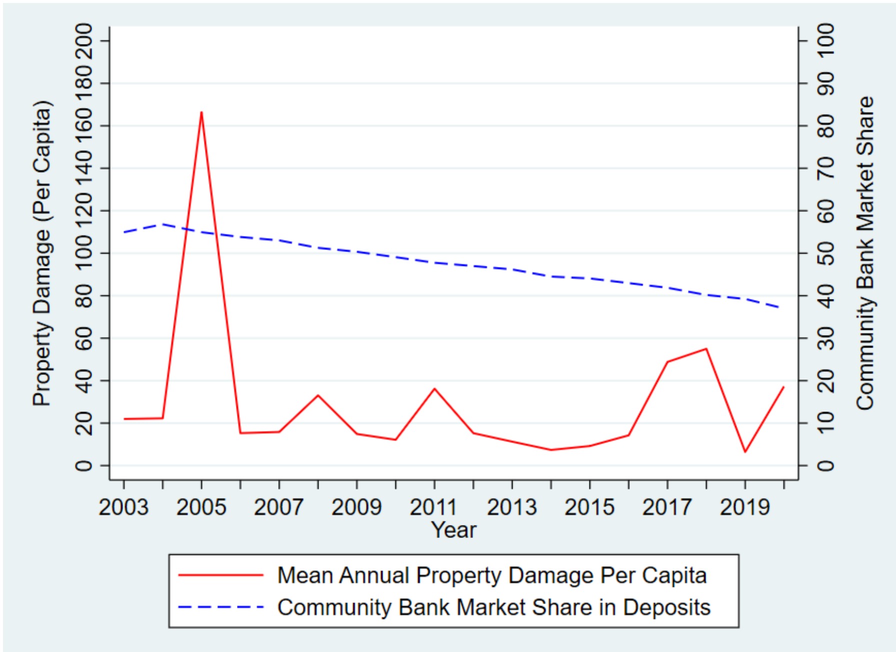
The gradual decline of community banks and the concurrent decrease in local economic resilience further raises important policy questions. Recovery costs are borne by a financial network of government programs, financial institutions, private citizens, and firms. As community banks dwindle, this weakens one component of the financial network that smooths credit demand, pushing costs from banks onto government programs, private citizens, and firms. It also reduces the capacity of regions to recover independently. With extreme weather events projected to become more frequent and severe as climate change progresses (IPCC, 2022), this implies rising costs for state- and federal-level disaster response and social security systems in the future, alongside the costs of increasing damages to state-owned physical assets and infrastructures.

A related question is how changing patterns of extreme weather events will shape the local banking markets themselves. If the risks associated with climate change become uninsurable in certain regions (Collier *et al.*, 2021), this may have significant consequences for banks' capacity to buffer such shocks and for the viability of a local, relationship-based banking structure as a whole. Moreover, compounding shocks could potentially overwhelm the capacity of local banks to engage in recovery lending (Dunz *et al.*, 2023), further threatening economic resilience. We encourage future research to carefully track developments and consider these questions.

Community banks' market shares are declining, while extreme weather events are becoming more destructive. The consolidation of the banking industry is driven by efficiency and profitability considerations in normal times. Our research demonstrates that smaller, community-oriented banks create important positive externalities when maintaining credit and thereby employment levels after extreme weather events. When faced with the increasing fury of *the Tempestates*, we should cherish the *George Baileys* of our world.

Figures

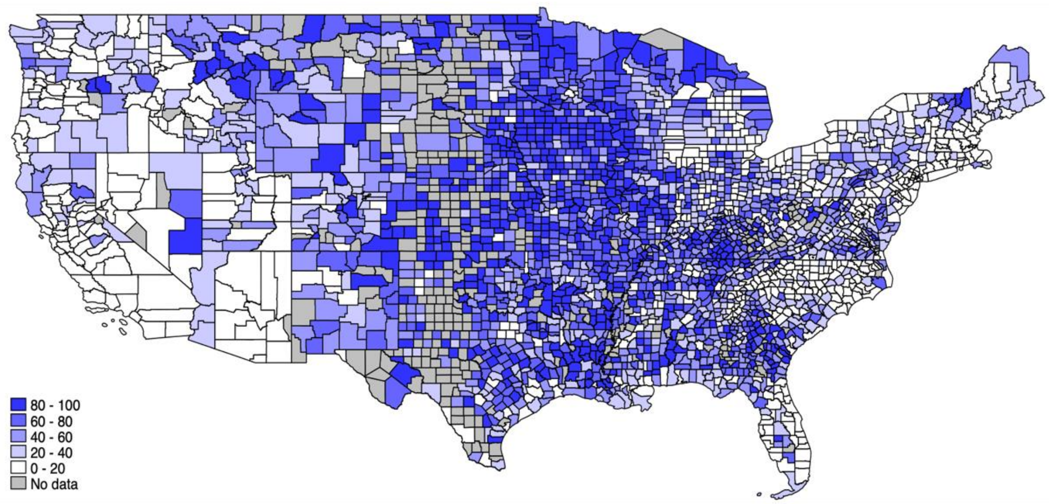
Figure 1: Trends in Extreme Weather Damages and Community Bank Market Shares (2003-2020).



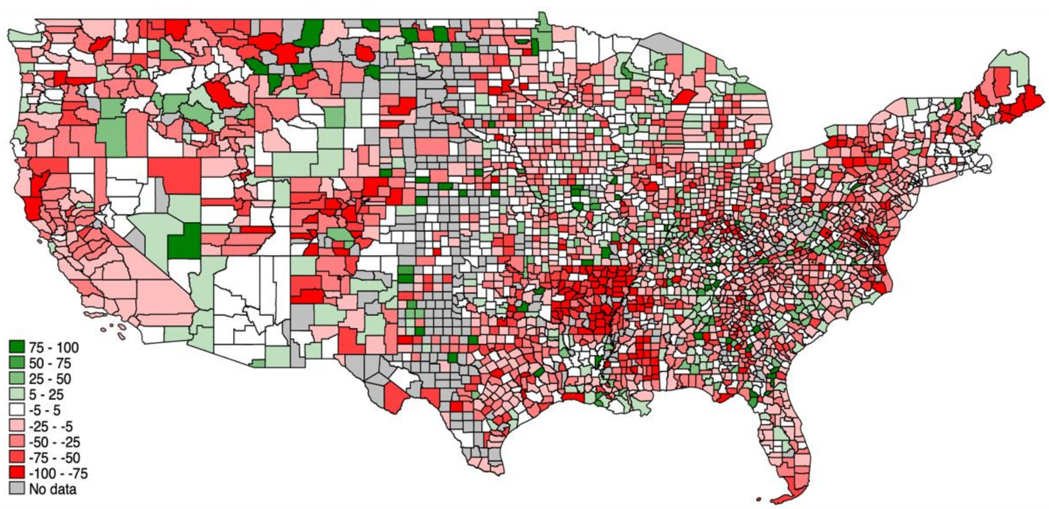
Notes: Figure 1 plots the mean annual per capita property damages (solid red line) and the mean annual deposit market shares of community bank (dashed blue line) across all counties in our sample between 2003 and 2020.

Figure 2: Community Bank Market Shares and Extreme Weather Damages across the US.

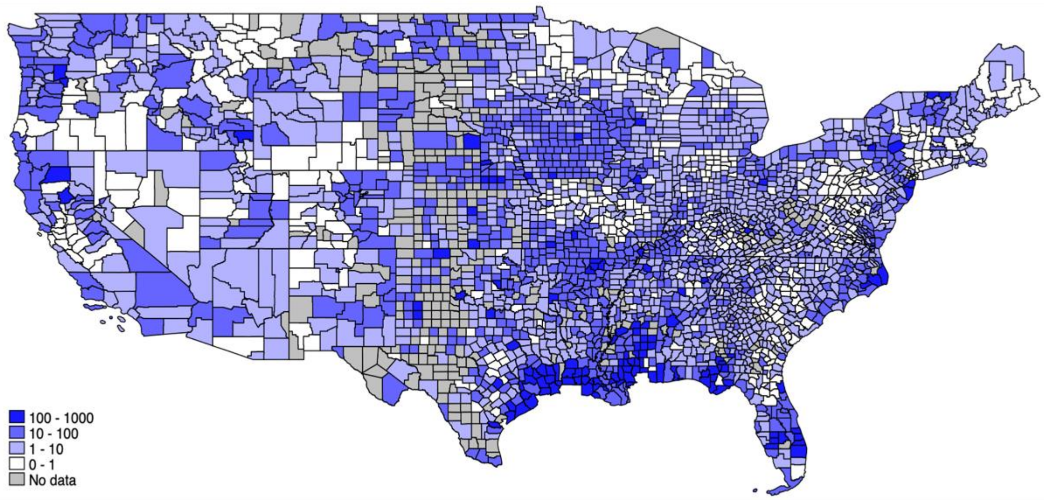
A: Community Bank Market Share (Mean; 2003-2020).



B: Community Bank Market Share (Change; 2003-2020).



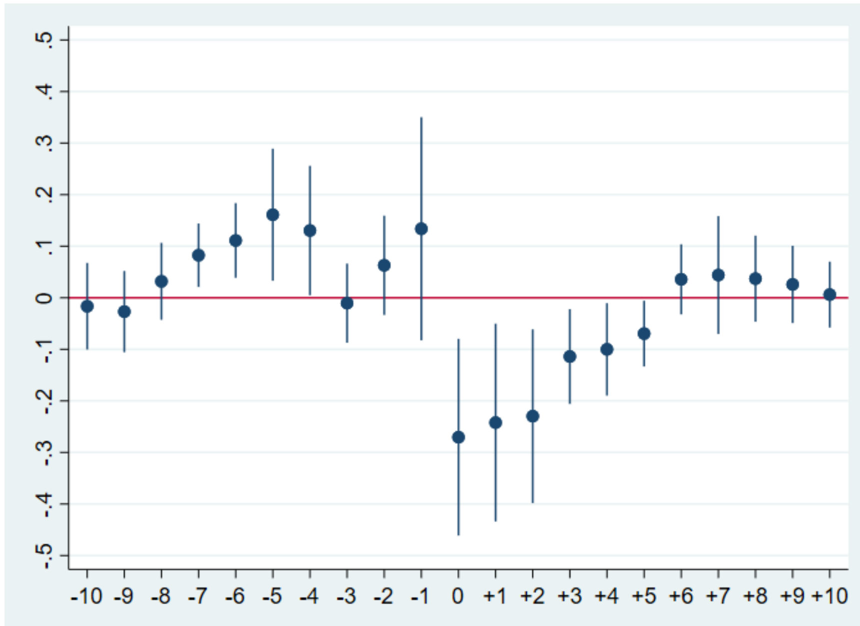
C: Extreme Weather Property Damage (Mean; 2003-2020).



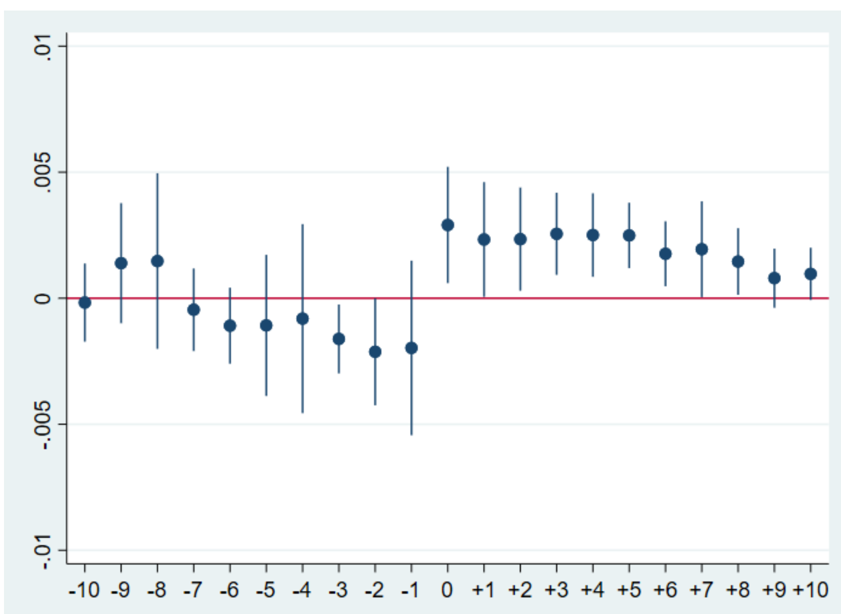
Notes: Figure 2A provides the mean market share of community banks, which represents the proportion of deposits held by community banks. Figure 2B provides the change in the community bank market share over the time period of interest (2003-2020). Figure 2C provides the mean per capita value of property damage by extreme weather. Each are calculated over the 2003-2020 time period.

Figure 3: The Effect of Property Damage and Community Banks on Employment Growth.

A: Property Damage.



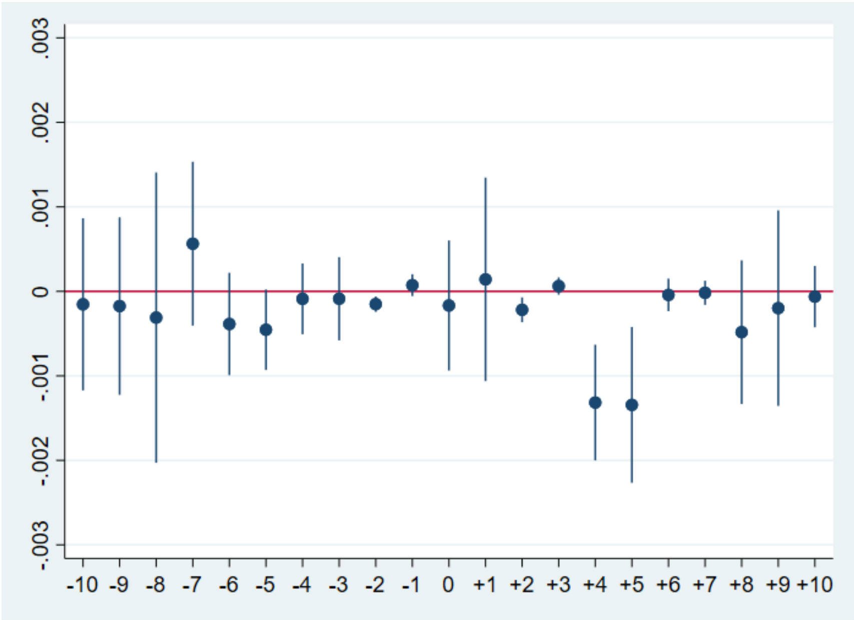
B: Property Damage × Community Bank Share.



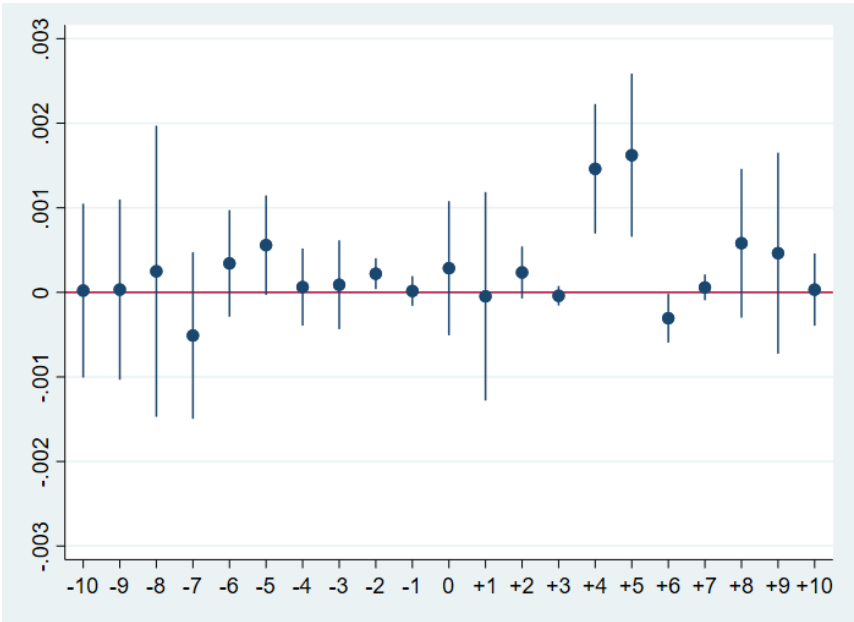
Note: Figure 3 provides the property damage and property damage × community bank share (leads and lags) coefficient estimates. The confidence intervals reflect the 90th percentile ranges. The complete model results are provided in Table A1. To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Figure 4: The Effect of Property Damage and Community Banks on Small Business Lending.

A: Property Damage.



B: Property Damage × Community Bank Indicator.



Note: Figure 4 provides the property damage and property damage × community bank share (leads and lags) coefficient estimates. The confidence intervals reflect the 90th percentile ranges. The complete model results are provided in Table A6.

Tables

Table 1A: Variable Definitions: County-level Data.

Name	Definition	Source
Employment Growth	The quarter-over-quarter percent change in the number of employees. The dataset used to observe employment, the QWI, is limited to employment by state and local governments and private firms.	Quarterly Workforce Indicators (QWI)
Community Bank Market Share	The proportion of deposits held by banks with less than $1 billion in total assets.	Summary of Deposits
Event Severity	The per capita value of property damage. SHELDUS hazard types: Coastal, Drought, Flood, Fog, Hail, Heat, Hurricane/Tropical Storm, Landslide, Lightning, Severe Thunderstorm, Tornado, Tsunami/Seiche, Wildfire, Wind, Winter Weather.	Spatial Hazard Events and Losses Database for the United States (SHELDUS)
Female	The proportion of residents classified as female.	Census Bureau
Working Age (25-64)	The proportion of residents between the ages of 25 and 64.	
Bachelors	The proportion of residents age 25 years and older holding a bachelor's degree.	
African-American	The proportion of residents classified as African-American.	
Asian	The proportion of residents classified as Asian.	
Other	The proportion of residents classified as Other Race.	
Hispanic	The proportion of residents classified as Hispanic.	
Median Household Income	The median household income.	
Foreign-Born	The proportion of residents identified as foreign born.	
Population Density	The number of residents per square kilometer.	
Industrial Compositions	The proportion of workers employed in each the manufacturing (2-digit NAICS Code: 31-33), services (71, 72) and public administration (92) industries.	Quarterly Census of. Employment and Wages (QCEW)
SME Employment Share	The proportion of workers employed by small and medium sized firms (< 500 employees).	QWI
Housing Price Index	The FHFA annual Housing Price Index. This variable captures differences in housing costs across space and time.	Federal Housing Finance Agency (FHFA)
Non-Disaster Related Deaths	The per capita number of deaths not caused by extreme weather.	SHELDUS, CDC Multiple Cause of Death (MCOD)
Insurance Policies	The per capita number of flood insurance policies.	FEMA

Notes: In the county-level dataset, the branch-level values are aggreggated to the county-level by weighting each branch by deposits.

Table 1B. Variable Definitions: Bank-level Data.

Variable	Definition	Source
Small Business Lending Growth	The quarter-over-quarter percent change in small business lending.	Call Reports
Herfindahl–Hirschman Index	The HHI, calculated using branch deposits.	Summary of Deposits
Capital Adequacy	The mean equity ratio, defined as the ratio of total equity capital to total assets.	Call Reports
Asset Quality	The mean nonperforming loans to total loans ratio. Nonperforming loans are defined as loans, or leases past due more than 90 days or are no longer accruing interest.	
Management Quality	The mean overhead costs ratio. The overhead costs ratio is defined as the ratio of premises, and fixed assets expenses to total income.	
Earnings	The mean return on assets. The return on assets ratio is defined as the ratio of total interest, and non-interest income to total assets.	
Liquidity	The mean ratio of liquid assets to total assets. Liquid assets included here are Currency and Coin, Money Market Mutual Funds, and Total Investment Securities.	
Sensitivity to Market Risk	The mean ratio of the absolute difference (gap) between short-term assets and short-term liabilities to gross total assets.	
Bank Age	The number of years the bank has been operating.	
Deposits Ratio	The ratio of deposits to total assets.	
Fee to Income Ratio	The ratio of noninterest to total income.	
Income Diversity	1 - abs(((Total Interest Income – Interest Expense) – (Noninterest Income- Noninterest Expense))/ Operating Income	
OCC Regulation	An indicator variable equal to one if the bank is regulated by the OCC, and zero otherwise.	
FDIC Regulation	An indicator variable equal to one if the bank is regulated by the FDIC, and zero otherwise.	
Federal Reserve Regulation	An indicator variable equal to one if the bank is regulated by the Federal Reserve, and zero otherwise.	
Total Loans to Assets	The proportion of grand total assets devoted to total loans.	
Deposits	The log of the per capita value of the deposits.	Summary of Deposits
Deposits in Metropolitan Regions	The proportion of deposits held by banks with the majority of their deposits in metropolitan areas.	
Bank Holding Company Ownership	The proportion of bank branches in a Bank Holding Company.	
Foreign Ownership	The proportion of bank branches that are foreign owned.	

Notes: In the county-level dataset, the branch-level values are aggreggated to the county-level by weighting each branch by deposits.

Table 2A: Dependent and County Control Variable Summary Statistics by Community Bank Presence.

		Mean					Percentile				
		Overall	Community	No Community	Difference	SD	1	25	50	75	99
Overall Employment Growth		0.16	0.16	0.27	0.11***	1.00	-2.09	-0.30	0.14	0.58	2.93
Property Damage (per capita)		27.20	28.47	8.68	-19.78	1,564.24	0.00	0.00	0.00	0.44	211.56
Community Bank Share		47.49	50.74	0.00	-50.74***	34.55	0.00	14.44	45.66	79.37	100.00
Female		50.22	50.26	49.85	-0.41***	1.92	42.40	49.75	50.53	51.21	53.55
Working Age		51.49	51.48	51.76	0.29***	3.30	41.62	49.82	51.73	53.46	59.31
Bachelors' Degree		13.54	13.53	13.79	0.26***	5.97	5.55	9.37	12.10	16.13	34.00
African-American		8.84	8.81	9.38	0.56***	13.52	0.00	0.64	2.46	10.79	59.07
Asian		1.27	1.30	1.03	-0.27***	2.56	0.00	0.28	0.58	1.24	13.05
Other Race		1.32	1.21	2.99	1.78***	4.41	0.00	0.19	0.36	0.75	18.34
Hispanic		7.76	7.83	6.77	-1.06***	11.76	0.28	1.69	3.35	8.07	58.17
Median Household Income (Log)		10.89	10.89	10.87	-0.02***	0.24	10.40	10.74	10.88	11.02	11.55
Foreign Born		4.57	4.59	4.35	-0.24***	5.47	0.23	1.36	2.65	5.59	27.88
Housing Price Index		267.48	268.74	249.16	-19.59***	167.88	104.30	164.98	212.58	316.18	926.07
Population Density		1.13	1.15	0.88	-0.27***	6.81	0.01	0.10	0.22	0.55	13.68
Employment Share	*Manufacturing*	16.71	16.83	14.94	-1.89***	12.60	0.00	6.92	14.08	23.77	53.37
	Entertainment	1.42	1.41	1.67	0.26***	1.82	0.00	0.47	1.03	1.75	9.25
	Hotels and Food	9.24	9.24	9.31	0.06	5.85	0.00	6.57	9.18	11.81	29.26
	Public Administration	7.90	7.80	9.40	1.60***	6.41	0.15	3.99	6.19	9.79	33.18
Non-Disaster Deaths		22.40	22.50	20.94	-1.56***	9.75	0.00	17.55	23.45	28.66	42.56
Policy Count		36.94	38.77	10.17	-28.60***	722.11	0.00	0.00	0.00	3.00	417.00
SME Employment Share		61.68	61.38	66.18	4.80***	14.50	33.22	50.75	60.30	72.13	94.27
Observations		137,372	128,572	8,800							

Notes: This table provides summary statistics for the variables used in our county-level analysis (unit of analysis: county-quarter). The time period is 2003-2020. Variables using dollar amounts are expressed in real 2020 USD using the implicit GDP price deflator.

Table 2B: Bank Control Variable Summary Statistics by Community Bank Presence.

	Mean					Percentile				
	Overall	Community	No Community	Difference	SD	1	25	50	75	99
Overall Bank Access (Deposits, Log)	20.59	20.68	19.41	-1.27***	1.75	17.59	19.51	20.30	21.29	27.22
Bank HHI	0.18	0.18	0.29	0.12***	0.15	0.01	0.08	0.14	0.25	0.71
Capital Adequacy	10.76	10.74	11.11	0.37***	1.43	7.75	9.86	10.70	11.53	14.88
Asset Quality	0.89	0.90	0.93	0.04**	1.45	0.00	0.00	0.30	1.16	6.37
Management Quality	1.00	1.02	0.92	-0.09***	0.30	0.59	0.80	0.94	1.20	1.75
Earnings	0.85	0.86	0.82	-0.05***	0.83	-2.50	0.73	0.99	1.21	2.07
Liquidity	26.30	26.41	24.83	-1.58***	7.69	12.16	21.06	25.49	30.32	49.58
Sensitivity to Market Risk	16.91	17.17	13.17	-4.00***	8.46	3.87	10.02	15.14	22.92	38.69
Bank Age	96.03	95.39	105.33	9.93***	22.09	39.31	81.77	97.26	110.95	144.94
Bank Holding Company Owned	75.77	76.23	69.07	-7.16***	23.50	0.00	61.29	80.46	100.00	100.00
Foreign Ownership.	2.77	2.60	5.36	2.76***	8.24	0.00	0.00	0.00	0.00	42.93
OCC Regulation	37.26	36.47	48.91	12.44***	27.39	0.00	14.55	35.26	56.45	100.00
FDIC Regulation	45.11	45.79	35.24	-10.55***	28.05	0.00	22.97	43.80	64.80	100.00
Fee Income	20.86	20.51	26.16	5.66***	31.09	5.46	15.35	20.51	26.03	38.70
Income Diversity	4.32	3.96	9.74	5.78***	19.69	-41.33	-9.04	3.65	17.97	46.76
Deposits to Total Assets	17.64	18.07	11.36	-6.71***	8.77	4.10	10.59	16.58	23.44	40.56
Total Loans to Assets	63.10	63.06	63.77	0.71***	7.39	41.86	58.91	63.66	68.02	78.32
Deposits in Metropolitan Region	65.53	63.88	89.61	25.73***	35.09	0.00	35.04	77.21	100.00	100.00
Observations	137,372	128,572	8,800							

Notes: This table provides summary statistics for the variables used in our county-level analysis (unit of analysis: county-quarter). The time period is 2003-2020. Variables using dollar amounts are expressed in real 2020 USD using the implicit GDP price deflator.

Table 3A: Dependent and County Control Variable Summary Statistics by Community Bank Status.

		Mean					Percentile				
		Overall	Community	No Community	Difference	SD	1	25	50	75	99
Small Business Loans ($1,000s)		60.58	17.49	480.05	462.57***	590.82	0.68	6.17	12.64	27.15	619.71
Small Business Loan Growth (%)		1.96	1.97	1.93	-0.04	17.09	-43.74	-4.08	0.00	5.31	81.12
Property Damage		14.59	14.65	14.05	-0.60	243.26	0.00	0.00	0.03	0.61	214.08
Female		50.66	50.63	50.95	0.31***	1.13	47.05	50.17	50.78	51.32	52.68
Working Age		52.09	51.98	53.22	1.24***	2.73	43.40	50.73	52.50	53.83	57.67
Bachelors' Degree		17.78	17.41	21.43	4.02***	5.99	7.14	13.23	17.41	21.41	34.05
African-American		10.66	10.40	13.23	2.83***	11.54	0.21	2.27	6.67	15.10	51.71
Asian		3.01	2.73	5.77	3.04***	3.80	0.09	0.83	1.85	3.67	16.75
Other Race		0.84	0.85	0.76	-0.10***	2.06	0.05	0.24	0.36	0.66	9.11
Hispanic		11.76	11.13	17.96	6.83***	13.92	0.81	2.90	6.06	14.81	64.02
Median Household Income (Log)		11.00	11.00	11.09	0.10***	0.21	10.52	10.88	10.99	11.13	11.53
Foreign Born		8.47	7.83	14.79	6.96***	8.41	0.63	2.75	5.68	10.67	36.05
Housing Price Index		388.49	373.01	539.20	166.20***	202.87	136.46	253.22	344.93	453.83	1,164.53
Population Density		3.71	3.14	9.30	6.16***	11.67	0.05	0.34	1.05	3.72	34.44
Employment Share	*Manufacturing*	12.91	13.28	9.38	-3.90***	8.18	1.44	7.43	10.50	16.79	40.28
	Entertainment	1.57	1.56	1.72	0.17***	1.01	0.00	1.05	1.45	1.87	5.08
	Hotels and Food	9.94	9.97	9.63	-0.34***	3.21	0.00	8.32	9.48	11.14	21.18
	Public Administration	5.88	5.97	5.06	-0.91***	3.99	1.01	3.66	4.85	6.77	23.24
Non-Disaster Deaths		21.52	21.74	19.41	-2.33***	5.77	9.78	17.46	21.14	25.12	36.31
Policy Count		207.43	175.48	518.46	342.98***	1844.82	0.00	1.00	5.00	26.00	3843.00
SME Employment Share		52.35	52.79	48.11	-4.68***	10.47	34.32	45.79	51.15	57.56	81.51
Observations		158,017	143,295	14,722							

Notes: This table provides summary statistics for the variables used in our bank-level analysis (unit of analysis: bank-quarter). The time period is 2003-2020. Variables using dollar amounts are expressed in real 2020 USD using the implicit GDP price deflator.

Table 3B: Bank Control Variable Summary Statistics by Community Bank Status.

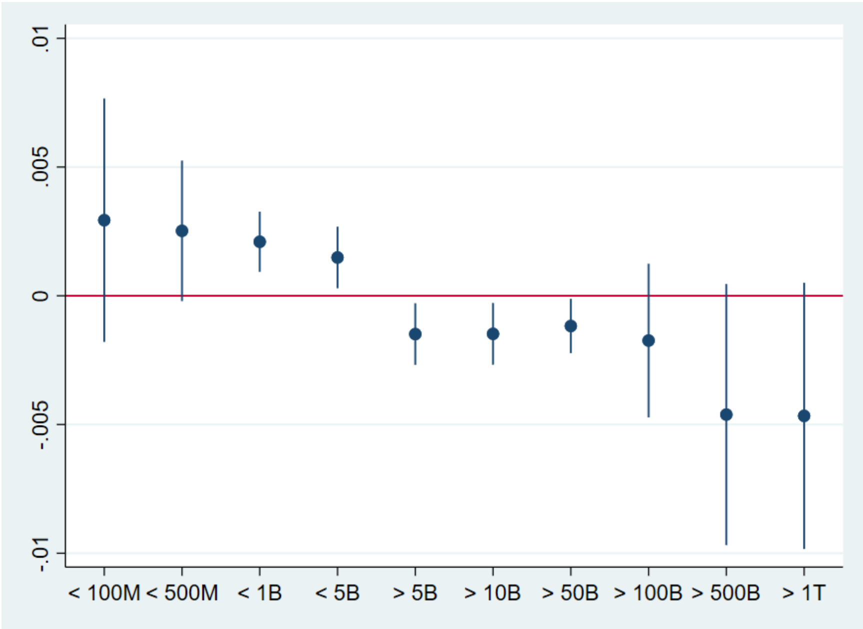
	Mean					Percentile				
	Overall	Community	No Community	Difference	SD	1	25	50	75	99
Bank HHI	0.09	0.10	0.07	-0.02***	0.09	0.01	0.04	0.07	0.12	0.50
Capital Adequacy	10.44	10.42	10.71	0.29***	2.85	5.14	8.76	9.96	11.57	20.12
Asset Quality	0.50	0.49	0.63	0.14***	1.51	0.00	0.00	0.00	0.11	7.23
Management Quality	1.01	1.02	0.93	-0.10***	0.40	0.46	0.78	0.95	1.18	2.18
Earnings	0.81	0.81	0.90	0.09***	1.31	-3.56	0.52	0.89	1.27	3.08
Liquidity	26.41	26.45	26.10	-0.35***	14.39	1.06	15.97	24.33	34.86	67.12
Sensitivity to Market Risk	17.96	18.13	16.39	-1.74***	11.75	0.40	8.81	16.26	25.27	50.49
Bank Age	70.06	69.27	77.84	8.58***	44.40	4.00	25.00	79.00	107.00	153.00
Bank Holding Company Owned	82.01	82.00	82.17	0.17	38.40	0.00	100.00	100.00	100.00	100.00
Foreign Ownership.	0.64	0.17	5.35	5.19***	8.03	0.00	0.00	0.00	0.00	0.00
OCC Regulation	21.23	20.42	29.15	8.73***	40.90	0.00	0.00	0.00	0.00	100.00
FDIC Regulation	64.33	66.03	47.82	-18.21***	47.90	0.00	0.00	100.00	100.00	100.00
Fee Income	15.48	14.95	20.77	5.83	569.08	-8.18	7.64	12.27	18.30	58.71
Income Diversity	-13.06	-14.52	1.15	15.68***	27.74	-100.00	-30.18	-14.03	4.46	59.52
Deposits to Total Assets	21.75	22.40	15.48	-6.92***	11.09	3.19	13.37	20.11	28.57	52.80
Total Loans to Assets	64.85	64.75	65.85	1.11***	13.90	26.02	56.53	66.64	75.00	89.45
Deposits in Metropolitan Region	67.00	64.65	89.89	25.24***	47.02	0.00	0.00	100.00	100.00	100.00
Observations	158,017	143,295	14,722							

Notes: This table provides summary statistics for the variables used in our bank-level analysis (unit of analysis: bank-quarter). The time period is 2003-2020. Variables using dollar amounts are expressed in real 2020 USD using the implicit GDP price deflator.

Appendix

Figures

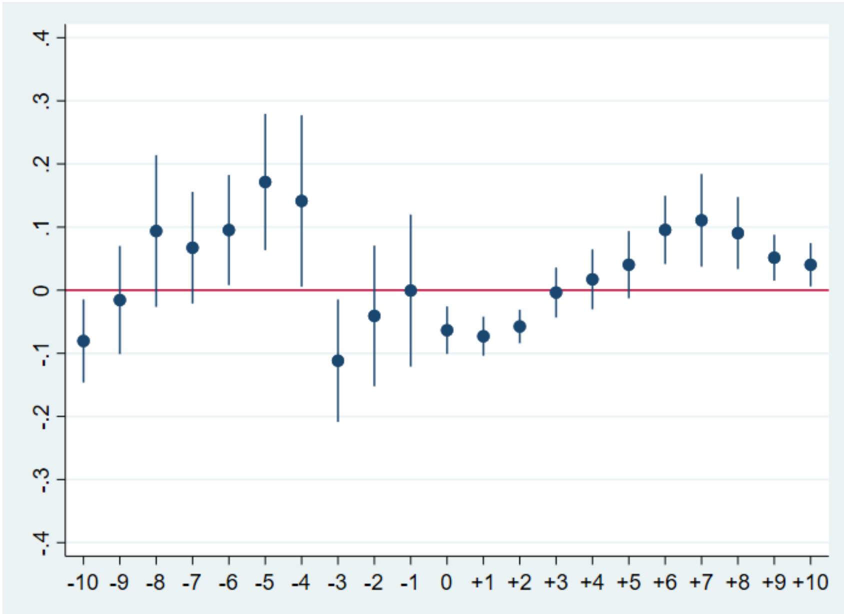
Figure A1: Property Damage × Market Share Coefficients by Bank Size.



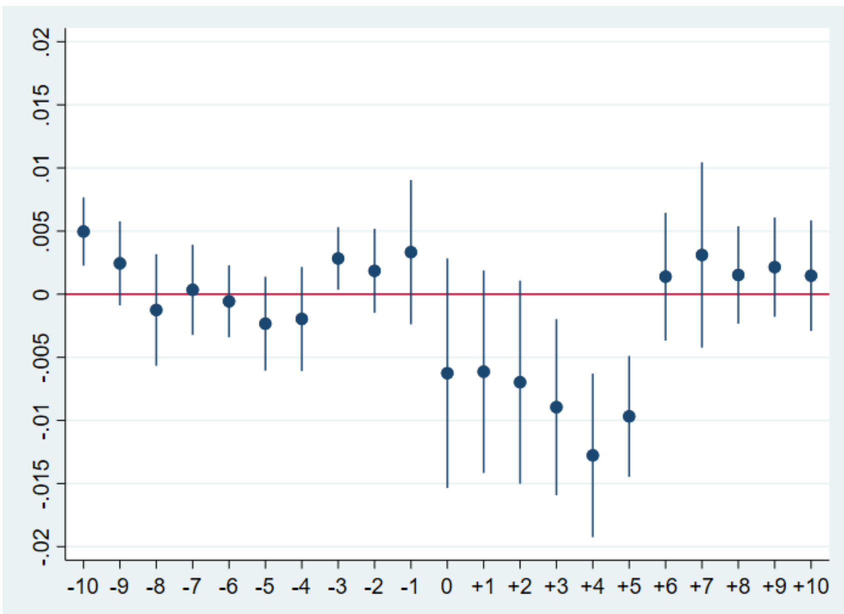
Note: This figure provides the property damage × deposit market share (fourth and fifth quarter lags) coefficient estimates for banks of different size groups. The first three estimates include all banks *smaller* than the stated threshold, i.e. the combined market shares of banks smaller than 100M, 500M, 1B, and 5B USD. All following estimates include banks *larger* than the stated thresholds, i.e. the combined market shares of banks larger than 5B, 10B, 50B, etc. The confidence intervals reflect the 90th percentile ranges. To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Figure A2: Top Four Banks - Coefficient Plots.

A: Property Damage.



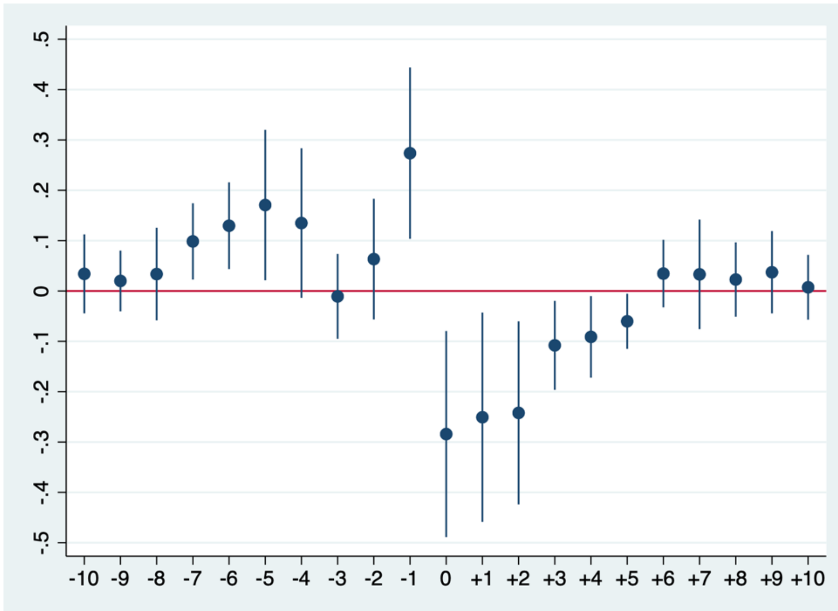
B: Property Damage × Top Four Bank Share.



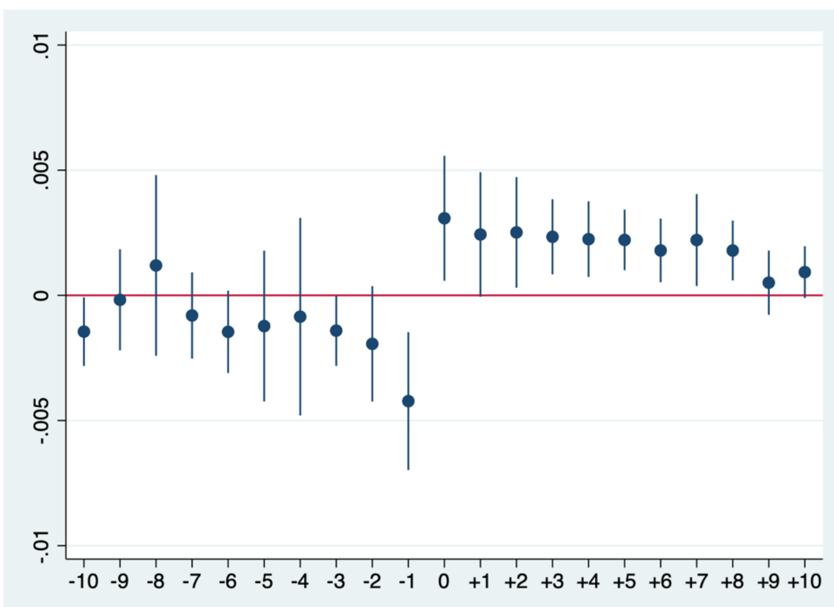
Notes: This figure provides the property damage and property damage × top-four bank share (leads and lags) coefficient estimates. The confidence intervals reflect the 90th percentile ranges. To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Figure A4: FDIC Community Bank Definition - Coefficient Plots.

A: Property Damage.



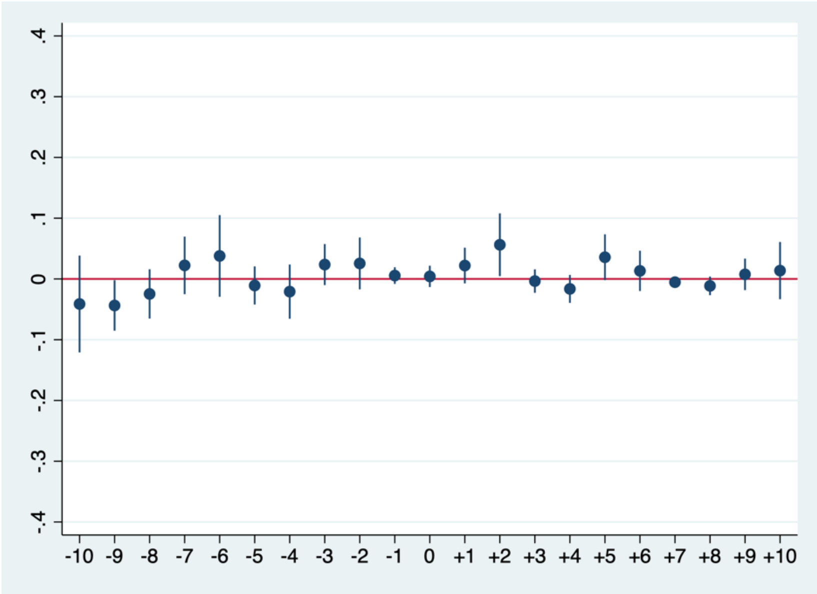
B: Property Damage × Community Bank Share.



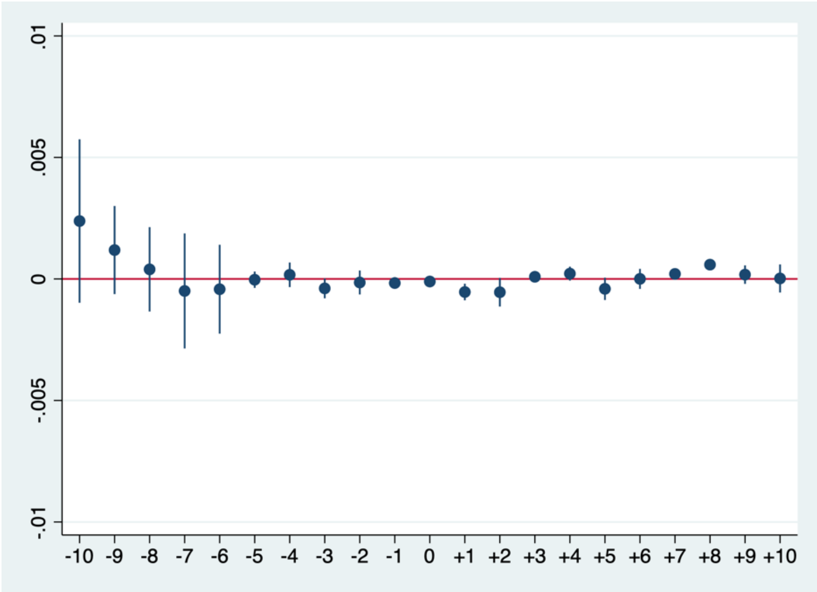
Note: This figure provides the property damage and property damage × community bank share (leads and lags) coefficient estimates. The confidence intervals reflect the 90th percentile ranges. The complete model results are provided in Table A1. To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Figure A5: County-Level Placebo Test - Coefficient Plots.

A: Property Damage.



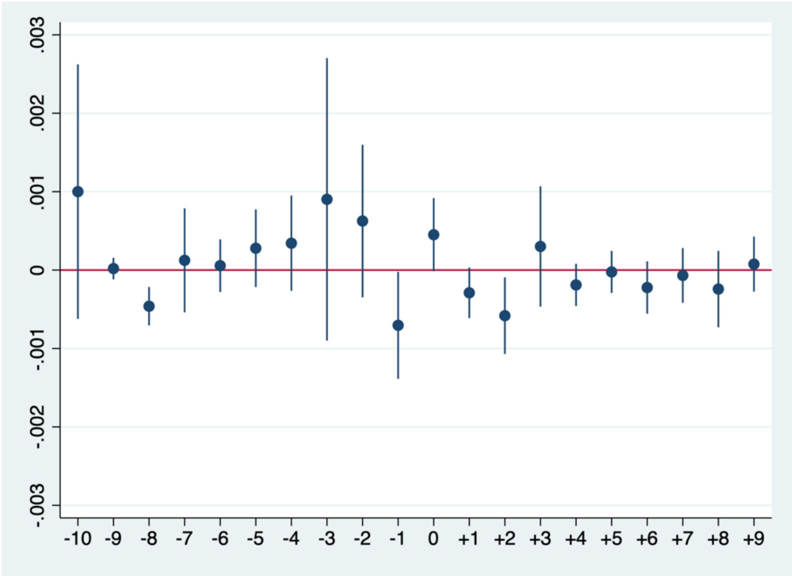
B: Property Damage × Community Bank Share.



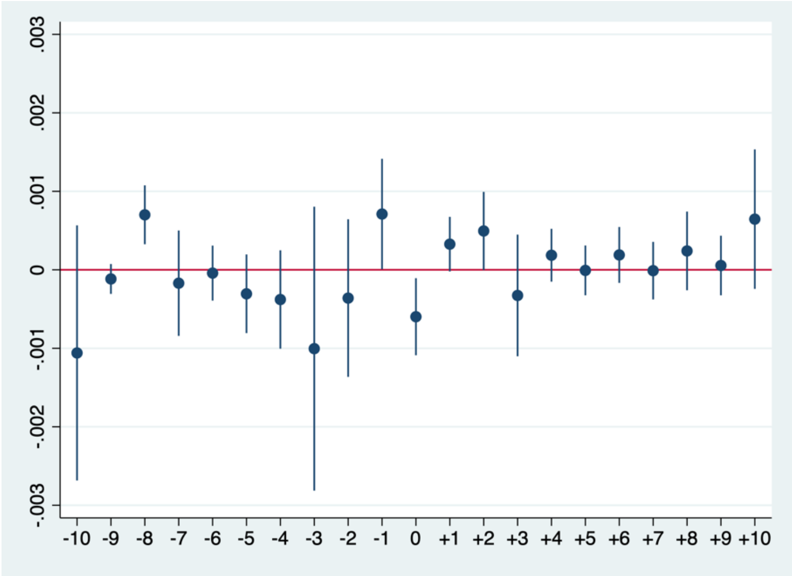
Notes: This figure provides the placebo property damage and property damage × community bank share (leads and lags) coefficient estimates. The confidence intervals reflect the 90th percentile ranges. To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Figure A6: Bank-Level Placebo Test - Coefficient Plots.

A: Property Damage.



B: Property Damage × Community Bank Indicator.



Notes: To adjust the coefficient estimates, the dependent variable has been multiplied by a factor of 10,000.

Tables

Table A1: Determinants of Community Bank Share.

	(1)	(2)	(3)	(4)
Female	-0.78**	-0.15	-0.039	-0.0083
	(0.31)	(0.15)	(0.32)	(0.26)
Working Age	-0.71***	-0.49***	0.18	0.10
	(0.19)	(0.11)	(0.17)	(0.15)
Bachelors' Degree	-0.47***	-0.44***	-0.58***	-0.47**
	(0.13)	(0.086)	(0.19)	(0.18)
African-American	-0.20***	-0.100***	-0.28	-0.28
	(0.042)	(0.027)	(0.28)	(0.24)
Asian	0.69**	0.027	0.38	0.21
	(0.32)	(0.19)	(0.48)	(0.42)
Other Race	-0.42***	-0.26***	-0.25	0.21
	(0.14)	(0.070)	(0.34)	(0.35)
Hispanic	0.17**	-0.012	-0.37	-0.17
	(0.069)	(0.053)	(0.27)	(0.22)
Median Household Income (Log)	5.37*	24.3***	1.29	0.85
	(3.13)	(2.01)	(3.59)	(3.42)
Foreign Born	-1.04***	-0.49***	-0.72**	-0.86***
	(0.20)	(0.13)	(0.29)	(0.26)
Housing Price Index	-0.051***	-0.0037	-0.00036	-0.0058**
	(0.0039)	(0.0023)	(0.0027)	(0.0025)
Population Density	0.14**	0.21***	0.28	0.087
	(0.073)	(0.060)	(1.00)	(1.06)
Manufacturing Employment Share	0.31***	0.11***	-0.055	-0.0078
	(0.050)	(0.029)	(0.043)	(0.040)
Entertainment Employment Share	-0.50*	0.066	-0.022	-0.084
	(0.30)	(0.15)	(0.17)	(0.16)
Hotels and Food Employment Share	-0.42***	-0.020	0.052	0.057
	(0.095)	(0.056)	(0.061)	(0.060)
Public Administration Employment Share	0.18*	0.16***	-0.016	-0.013
	(0.098)	(0.057)	(0.069)	(0.068)
Non-Disaster Deaths	-0.14***	-0.026	-0.0053	-0.0062
	(0.049)	(0.030)	(0.0093)	(0.0087)
Policy Count	0.00010	0.00026**	-0.000039	0.0000061
	(0.00023)	(0.00011)	(0.000055)	(0.000045)
SME Employment Share	0.47***	0.067***	0.046	0.020
	(0.040)	(0.026)	(0.030)	(0.026)

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Bank HHI		-5.37*		2.98
		(2.77)		(6.52)
Capital Adequacy		-0.70***		-1.04***
		(0.19)		(0.19)
Asset Quality		-0.47**		-0.090
		(0.19)		(0.14)
Management Quality		10.5***		3.35***
		(1.46)		(0.63)
Earnings		6.06***		2.37***
		(0.33)		(0.16)
Liquidity		0.43***		0.0044
		(0.073)		(0.060)
Sensitivity to Market Risk		-1.02***		-0.40***
		(0.081)		(0.053)
Bank Age		-0.031*		-0.11***
		(0.016)		(0.024)
Bank Holding Company Owned		0.022*		0.013
		(0.013)		(0.012)
Foreign Ownership.		-0.26***		-0.11***
		(0.029)		(0.025)
OCC Regulation		0.043**		-0.0010
		(0.018)		(0.022)
FDIC Regulation		0.10***		0.069**
		(0.019)		(0.027)
Fee Income		-0.0060*		-0.00039
		(0.0034)		(0.00082)
Income Diversity		-0.57***		-0.30***
		(0.026)		(0.019)
Deposits to Total Assets		2.26***		1.30***
		(0.089)		(0.083)
Total Loans to Assets		0.035		-0.087
		(0.075)		(0.065)
Deposits in Metropolitan Region		-0.29***		-0.33***
		(0.013)		(0.018)
County FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clusters	2,750	2,750	2,748	2,748
Observations	137,372	137,372	137,370	137,370
R^2	0.28	0.67	0.84	0.87
F-Stat	102.5***	513.5***	1.53*	52.0***

Notes: Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The sample period is 2003-2020.

Table A2: The Effect of Property Damage and Community Banks on Employment Growth – Preferred specification (Model 1) and alternative specifications.

		(1)	(2)	(3)	(4)
Event Severity		Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita	Fatalities
Community Bank Share		-1.20	-8.39**	2.12	-1.70
		(3.98)	(3.48)	(3.94)	(3.84)
Property Damage	-10	-0.016	-0.018	-0.017	7.48
		(0.051)	(0.042)	(0.048)	(8.12)
	-9	-0.027	-0.026	-0.026	15.8**
		(0.048)	(0.043)	(0.046)	(7.98)
	-8	0.032	0.020	0.029	20.6**
		(0.045)	(0.044)	(0.045)	(10.3)
	-7	0.083**	0.075*	0.081**	-1.38
		(0.037)	(0.040)	(0.038)	(5.27)
	-6	0.11**	0.11**	0.11**	-4.16
		(0.044)	(0.046)	(0.045)	(4.72)
	-5	0.16**	0.15*	0.16**	3.43
		(0.078)	(0.083)	(0.080)	(4.89)
	-4	0.13*	0.12	0.13	19.9
		(0.076)	(0.079)	(0.079)	(12.2)
	-3	-0.011	-0.030	-0.017	0.28
		(0.047)	(0.044)	(0.045)	(9.36)
	-2	0.063	0.035	0.055	-11.9**
		(0.059)	(0.056)	(0.058)	(5.44)
	-1	0.13	0.12	0.14	-1.88
		(0.13)	(0.13)	(0.13)	(5.68)
	0	-0.27**	-0.29**	-0.27**	-14.6
		(0.12)	(0.12)	(0.11)	(10.6)
	+1	-0.24**	-0.26**	-0.24**	-20.2**
		(0.12)	(0.12)	(0.12)	(8.31)
	+2	-0.23**	-0.23**	-0.23**	-20.4***
		(0.10)	(0.10)	(0.10)	(6.66)
	+3	-0.11**	-0.11**	-0.11**	-14.0**
		(0.056)	(0.054)	(0.055)	(6.63)
	+4	-0.10*	-0.096*	-0.100*	-11.0
		(0.054)	(0.054)	(0.053)	(7.96)
	+5	-0.069*	-0.067*	-0.070*	-14.3***
		(0.039)	(0.039)	(0.038)	(4.01)
	+6	0.036	0.038	0.035	2.83
		(0.041)	(0.044)	(0.042)	(4.32)
	+7	0.044	0.046	0.043	12.4***
		(0.069)	(0.071)	(0.070)	(3.76)
	+8	0.037	0.041	0.037	12.1**
		(0.051)	(0.053)	(0.052)	(5.55)
	+9	0.026	0.029	0.025	6.66
		(0.046)	(0.047)	(0.046)	(4.24)
	+10	0.0061	0.0082	0.0049	5.74
		(0.039)	(0.040)	(0.040)	(4.06)

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Community Bank Share × Property Damage	-10	-0.00017	-0.00034	-0.00024	-0.13
		(0.00094)	(0.00087)	(0.00092)	(0.098)
	-9	0.0014	0.0010	0.0013	-0.19**
		(0.0014)	(0.0015)	(0.0015)	(0.097)
	-8	0.0015	0.0012	0.0014	-0.18
		(0.0021)	(0.0022)	(0.0021)	(0.13)
	-7	-0.00046	-0.00076	-0.00051	0.11
		(0.00100)	(0.0010)	(0.0010)	(0.074)
	-6	-0.0011	-0.0014	-0.0011	0.0031
		(0.00092)	(0.00094)	(0.00093)	(0.054)
	-5	-0.0011	-0.0011	-0.0011	-0.016
		(0.0017)	(0.0018)	(0.0018)	(0.053)
	-4	-0.00081	-0.00077	-0.00077	-0.16
		(0.0023)	(0.0024)	(0.0023)	(0.14)
	-3	-0.0016*	-0.0015*	-0.0016**	0.086
		(0.00083)	(0.00078)	(0.00080)	(0.13)
	-2	-0.0021	-0.0020*	-0.0021	0.11
		(0.0013)	(0.0012)	(0.0013)	(0.066)
	-1	-0.0020	-0.0019	-0.0021	0.075
		(0.0021)	(0.0021)	(0.0021)	(0.069)
	0	0.0029**	0.0033**	0.0029**	0.28**
		(0.0014)	(0.0014)	(0.0014)	(0.12)
	+1	0.0023*	0.0027*	0.0023*	0.35***
		(0.0014)	(0.0014)	(0.0014)	(0.089)
	+2	0.0023*	0.0025**	0.0023*	0.23**
		(0.0012)	(0.0013)	(0.0012)	(0.094)
	+3	0.0026***	0.0026***	0.0026***	0.22***
		(0.00099)	(0.00096)	(0.00098)	(0.083)
	+4	0.0025**	0.0026***	0.0026***	0.23**
		(0.0010)	(0.0010)	(0.00099)	(0.10)
	+5	0.0025***	0.0026***	0.0026***	0.29***
		(0.00079)	(0.00081)	(0.00078)	(0.058)
	+6	0.0018**	0.0019**	0.0018**	-0.024
		(0.00078)	(0.00083)	(0.00080)	(0.067)
	+7	0.0019*	0.0021*	0.0020*	-0.085
		(0.0012)	(0.0012)	(0.0012)	(0.052)
	+8	0.0015*	0.0015*	0.0015*	-0.043
		(0.00080)	(0.00084)	(0.00082)	(0.087)
	+9	0.00080	0.00091	0.00084	-0.00095
		(0.00071)	(0.00072)	(0.00072)	(0.066)
	+10	0.00097	0.0011*	0.00100	-0.13***
		(0.00063)	(0.00064)	(0.00065)	(0.050)
State-Quarter FE		Yes	Yes	Yes	Yes
County Controls		Yes	Yes	No	Yes
Bank Controls		Yes	No	No	Yes
Only counties with events		No	No	No	No
Method		OLS	OLS	OLS	OLS
Clusters		2,750	2,750	2,750	2,750
Observations		137,372	137,372	137,372	137,372
R^2		0.25	0.22	0.25	0.25
F-Statistic		28.25***	30.74***	34.04***	10.63***

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		(5)	(6)	(7)	(8)
Event Severity		Property Damage Per GDP	Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita
Community Bank Share		-1.74	-0.19	-0.95	-0.53
		(4.01)	(4.20)	(4.40)	(4.51)
Property Damage	-10	-0.53	0.011	0.019	0.071
		(1.32)	(0.055)	(0.057)	(0.057)
	-9	-0.15	-0.054	-0.013	-0.040
		(0.88)	(0.076)	(0.057)	(0.10)
	-8	0.82	0.11^{*}	0.029	0.10
		(1.16)	(0.058)	(0.051)	(0.081)
	-7	2.08^{*}	0.093	0.063^{**}	0.045
		(1.08)	(0.062)	(0.031)	(0.051)
	-6	2.79^{**}	0.098	0.086^{**}	0.039
		(1.25)	(0.075)	(0.034)	(0.046)
	-5	4.74^{**}	0.22^{***}	0.11^{*}	0.14
		(2.15)	(0.083)	(0.063)	(0.087)
	-4	4.20^{*}	0.017	0.057	-0.013
		(2.25)	(0.098)	(0.053)	(0.099)
	-3	-1.68	0.018	-0.015	-0.0021
		(1.84)	(0.037)	(0.048)	(0.034)
	-2	0.85	0.0033	0.020	-0.046
		(2.03)	(0.056)	(0.063)	(0.073)
	-1	1.58	0.059	-0.0038	-0.080
		(3.51)	(0.13)	(0.12)	(0.11)
	0	-10.4^{**}	-0.29^{**}	-0.089^{**}	-0.11^{***}
		(4.99)	(0.12)	(0.035)	(0.033)
	+1	-9.98^{**}	-0.29^{**}	-0.051	-0.054^{***}
		(4.54)	(0.13)	(0.036)	(0.017)
	+2	-5.86^{*}	-0.26^{**}	-0.24^{**}	-0.26^{**}
		(3.31)	(0.10)	(0.10)	(0.10)
	+3	-3.61^{**}	-0.088	-0.12^{**}	-0.087
		(1.54)	(0.057)	(0.057)	(0.0572)
	+4	-4.03^{**}	-0.10^{*}	-0.10^{*}	-0.10^{*}
		(2.03)	(0.055)	(0.056)	(0.056)
	+5	-2.90^{*}	-0.069^{*}	-0.069^{*}	-0.070^{*}
		(1.51)	(0.038)	(0.039)	(0.039)
	+6	6.12^{**}	0.18^{*}	0.037	0.19^{*}
		(2.72)	(0.10)	(0.042)	(0.11)
	+7	5.16	0.31^{***}	0.039	0.30^{***}
		(4.38)	(0.11)	(0.067)	(0.11)
	+8	3.51	0.21^{**}	0.030	0.20^{*}
		(4.06)	(0.11)	(0.047)	(0.11)
	+9	-0.35	-0.0093	0.033	-0.00028
		(3.59)	(0.022)	(0.048)	(0.024)
	+10	0.037	-0.017	0.011	-0.012
		(3.30)	(0.031)	(0.040)	(0.031)

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Community Bank Share × Property Damage	-10	0.0016	-0.00039	-0.00080	-0.0014
		(0.022)	(0.00099)	(0.0010)	(0.00097)
	-9	0.025	0.00080	0.0011	0.00051
		(0.029)	(0.0015)	(0.0016)	(0.0019)
	-8	0.027	-0.00079	0.0016	-0.00069
		(0.049)	(0.0010)	(0.0022)	(0.0012)
	-7	-0.011	-0.00050	-0.00014	0.00035
		(0.022)	(0.0015)	(0.00096)	(0.0015)
	-6	-0.016	-0.0014	-0.00070	-0.00048
		(0.021)	(0.0013)	(0.00082)	(0.0011)
	-5	-0.030	-0.0011	-0.00017	0.00040
		(0.039)	(0.0022)	(0.0016)	(0.0024)
	-4	-0.025	0.0014	0.00052	0.0020
		(0.051)	(0.0031)	(0.0022)	(0.0031)
	-3	-0.0020	-0.0011	-0.0015*	-0.00070
		(0.024)	(0.0010)	(0.00084)	(0.0011)
	-2	-0.028	-0.00022	-0.0015	0.00058
		(0.031)	(0.0012)	(0.0013)	(0.0012)
	-1	-0.022	-0.00052	0.00018	0.0018
		(0.045)	(0.0022)	(0.0021)	(0.0023)
	0	0.10*	0.0032**	0.00062	0.00094**
		(0.060)	(0.0014)	(0.00045)	(0.00046)
	+1	0.081	0.0029*	-0.000071	-0.000050
		(0.055)	(0.0016)	(0.00046)	(0.00020)
	+2	0.053	0.0027**	0.0025**	0.0028**
		(0.049)	(0.0013)	(0.0012)	(0.0013)
	+3	0.084***	0.00012	0.0026**	0.000033
		(0.030)	(0.0024)	(0.0010)	(0.0024)
	+4	0.11**	0.0025**	0.0025**	0.0026**
		(0.052)	(0.0010)	(0.0010)	(0.0011)
	+5	0.097**	0.0025***	0.0025***	0.0025***
		(0.047)	(0.00077)	(0.00080)	(0.00078)
	+6	0.0015	-0.00083	0.0017**	-0.00088
		(0.051)	(0.0019)	(0.00078)	(0.0019)
	+7	0.052	-0.0026	0.0020*	-0.0024
		(0.084)	(0.0018)	(0.0011)	(0.0018)
	+8	0.038	-0.0014	0.0016**	-0.0011
		(0.081)	(0.0016)	(0.00073)	(0.0016)
	+9	0.065	0.0012***	0.00064	0.0011***
		(0.064)	(0.00033)	(0.00074)	(0.00035)
	+10	0.057	0.0012	0.00083	0.00087
		(0.062)	(0.0015)	(0.00064)	(0.0015)
State-Quarter FE		Yes	Yes	Yes	Yes
County Controls		Yes	Yes	Yes	Yes
Bank Controls		Yes	Yes	Yes	Yes
Only counties with events		No	Yes	No	Yes
Method		OLS	OLS	PSM	PSM
Clusters		2,700	2,737	2,602	2,576
Observations		134,801	84,803	124,647	78,111
R^2		0.254	0.284	0.257	0.290
F-Stat		11.33***	31.83***	34.72***	34.18***

Notes: Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The sample period is 2003-2020.

Table A3: Firm Size Coefficient Estimates.

	All Firm Sizes	0-19 Employees	20-49 Employees
Community Bank Share	1.55	-8.95	5.27
	(3.49)	(7.71)	(14.5)
Property Damage	-0.065**	0.027	-0.075
	(0.032)	(0.034)	(0.063)
Community Bank Share × Property Damage	0.0021***	0.00097	0.00040
	(0.00071)	(0.0011)	(0.0015)
State-Quarter FE	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Clusters	2,763	2,763	2,763
Observations	178,741	178,741	178,741
R^2	0.271	0.345	0.0782
F-Stat	16.06***	8.110***	8.066***

	50-249 Employees	250-499 Employees	500+ Employees
Community Bank Share	-17.4	32.5	8.95
	(25.4)	(117.3)	(20.3)
Property Damage	-0.058	1.22	-0.11*
	(0.17)	(1.10)	(0.060)
Community Bank Share × Property Damage	0.0011	-0.034	0.0049**
	(0.0026)	(0.023)	(0.0021)
State-Quarter FE	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Clusters	2,763	2,763	2,763
Observations	178,741	178,741	178,741
R^2	0.0608	0.0251	0.0654
F-Stat	6.96***	4.848***	7.699***

Notes: The property damage variable is constructed using the sum of the fourth and fifth quarter lagging variable. Standard errors clustered at the county level. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period is 2003-2020.

Table A4: Disaster Coefficient Estimates.

	Overall	Coastal	Drought	Flooding	Heat	Hurricane
Community Bank Share	1.55	1.65	1.65	1.66	1.64	1.61
	(3.49)	(3.45)	(3.49)	(3.48)	(3.49)	(3.49)
Property Damage	-0.065**	0.14	0.066	-0.067	-11.5***	-0.097*
	(0.032)	(9.31)	(0.41)	(0.093)	(4.06)	(0.052)
Community Bank Share × Property Damage	0.0021***	1.09	-0.0046	-0.0024	0.17	0.0032***
	(0.00071)	(1.98)	(0.0074)	(0.0039)	(0.16)	(0.00087)
State-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	2,763	2,763	2,763	2,763	2,763	2,763
Observations	178,741	178,741	178,741	178,741	178,741	178,741
R^2	0.271	0.271	0.271	0.271	0.271	0.271
F-Stat	16.06***	16.06***	16.00***	15.98***	16.24***	17.22***

	TStorm	Tornado	Tsunami	Wildfire	Wind	Winter Weather
Community Bank Share	1.70	1.63	1.65	1.65	1.66	1.66
	(3.49)	(3.49)	(3.49)	(3.48)	(3.49)	(3.48)
Property Damage	2.59	-0.20	-5.79**	0.13***	0.15	0.39
	(1.60)	(0.13)	(2.34)	(0.048)	(1.34)	(0.35)
Community Bank Share × Property Damage	-0.027*	0.0035	1.28**	-0.0055**	-0.0028	-0.0024
	(0.016)	(0.0029)	(0.51)	(0.0025)	(0.013)	(0.0076)
State-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	2,763	2,763	2,763	2,763	2,763	2,763
Observations	178,741	178,741	178,741	178,741	178,741	178,741
R^2	0.271	0.271	0.271	0.271	0.271	0.271
F-Stat	16.43***	16.00***	16.18***	16.27***	16.47***	16.05***

Notes: The property damage variable is constructed using the sum of the fourth and fifth quarter lagging variable. Standard errors clustered at the county level. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The sample period is 2003-2020.

Table A5: Firm Age Coefficient Estimates

	All Firm Ages	0-1 Years	2-3 Years
Community Bank Share	1.55	-77.3	-54.6
	(3.49)	(48.0)	(50.9)
Property Damage	-0.065**	0.13	0.17
	(0.032)	(0.20)	(0.28)
Community Bank Share × Property Damage	0.0021***	0.00067	-0.0033
	(0.00071)	(0.0065)	(0.0057)
State-Quarter FE	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Clusters	2,763	2,763	2,763
Observations	178,741	178,741	178,741
R^2	0.271	0.0882	0.0465
F-Stat	16.06***	28.63***	21.10***

	4-5 Years	6-10 Years	11+ Years
Community Bank Share	-24.2	-20.4	5.15
	(34.2)	(17.3)	(5.66)
Property Damage	0.00056	-0.0035	-0.068**
	(0.21)	(0.12)	(0.034)
Community Bank Share × Property Damage	0.0044	-0.0014	0.0032***
	(0.0049)	(0.0033)	(0.0011)
State-Quarter FE	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Clusters	2,763	2,763	2,763
Observations	178,741	178,741	178,741
R^2	0.0595	0.0633	0.182
F-Stat	26.23***	13.21***	11.79***

Notes: The property damage variable is constructed using the sum of the fourth and fifth quarter lagging variable. Standard errors clustered at the county level. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The sample period is 2003-2020.

Table A6: The Effect of Community Bank Status on Small Business Lending Growth.

		(1)	(2)	(3)	(4)	(5)	(6)
Event Severity		Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita
Community Bank		-0.024	-0.027	-0.11	0.24	-0.098	1.55***
		(0.16)	(0.15)	(0.14)	(0.15)	(0.16)	(0.39)
Property Damage	-10	-0.00015	-0.000056	-0.00015	-0.00016	-0.00015	0.000041
		(0.00062)	(0.00061)	(0.00061)	(0.00061)	(0.00063)	(0.00064)
	-9	-0.00017	-0.00012	-0.00022	-0.00021	-0.00017	-0.00013
		(0.00064)	(0.00065)	(0.00064)	(0.00065)	(0.00063)	(0.00066)
	-8	-0.00031	-0.00083	-0.00041	-0.00038	-0.00032	-0.00025
		(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.00098)
	-7	0.00056	0.00053	0.00059	0.00060	0.00055	0.00070
		(0.00059)	(0.00062)	(0.00061)	(0.00061)	(0.00059)	(0.00060)
	-6	-0.00039	-0.00023	-0.00035	-0.00035	-0.00040	-0.00019
		(0.00037)	(0.00038)	(0.00036)	(0.00037)	(0.00037)	(0.00036)
	-5	-0.00045	-0.00042	-0.00043	-0.00042	-0.00045	-0.00036
		(0.00029)	(0.00032)	(0.00029)	(0.00030)	(0.00029)	(0.00031)
	-4	-0.000088	-0.00039	-0.00010	-0.000079	-0.000096	-0.000059
		(0.00025)	(0.00025)	(0.00024)	(0.00025)	(0.00025)	(0.00031)
	-3	-0.000087	0.000083	-0.000015	-0.000031	-0.000069	-0.00012
		(0.00030)	(0.00036)	(0.00031)	(0.00031)	(0.00030)	(0.00031)
	-2	-0.00015***	0.000028	-0.00016***	-0.00015***	-0.00015***	-0.00026***
		(0.000055)	(0.000078)	(0.000053)	(0.000053)	(0.000055)	(0.000059)
	-1	0.000073	-0.000015	0.000061	0.000078	0.000069	-0.000023
		(0.000078)	(0.000066)	(0.000080)	(0.000087)	(0.000074)	(0.000098)
	0	-0.00017	-0.00059	-0.00025	-0.00017	-0.00019	-0.000015
		(0.00047)	(0.00044)	(0.00046)	(0.00047)	(0.00046)	(0.00046)
	+1	0.00014	0.00053	0.00018	0.00018	0.00016	0.00019
		(0.00073)	(0.00082)	(0.00074)	(0.00074)	(0.00073)	(0.00069)
	+2	-0.00022**	-0.0000039	-0.00025***	-0.00025***	-0.00021**	-0.00031***
		(0.000089)	(0.000075)	(0.000083)	(0.000087)	(0.000083)	(0.000081)
	+3	0.000062	-0.000044	0.000046	0.000045	0.000071	-0.000024
		(0.000062)	(0.000061)	(0.000070)	(0.000067)	(0.000064)	(0.000082)
	+4	-0.0013***	-0.0015***	-0.0013***	-0.0013***	-0.0013***	-0.0012***
		(0.00042)	(0.00040)	(0.00041)	(0.00042)	(0.00042)	(0.00041)
	+5	-0.0013**	-0.00096	-0.0013**	-0.0013**	-0.0013**	-0.0012**
		(0.00056)	(0.00065)	(0.00058)	(0.00058)	(0.00056)	(0.00052)
	+6	-0.000042	0.00017	-0.000057	-0.000060	-0.000031	-0.00014
		(0.00012)	(0.00018)	(0.00013)	(0.00012)	(0.00012)	(0.00012)
	+7	-0.000017	-0.00011	-0.000022	-0.000023	-0.0000053	-0.00012
		(0.000086)	(0.000097)	(0.000081)	(0.000083)	(0.000083)	(0.000092)
	+8	-0.00048	-0.00059	-0.00048	-0.00043	-0.00046	-0.00031
		(0.00052)	(0.00044)	(0.00049)	(0.00052)	(0.00051)	(0.00041)
	+9	-0.00020	-0.00026	-0.00017	-0.00019	-0.00015	-0.000050
		(0.00070)	(0.00061)	(0.00070)	(0.00071)	(0.00070)	(0.00078)
	+10	-0.000063	0.00011	-0.000072	-0.000072	-0.000055	-0.00016
		(0.00022)	(0.00027)	(0.00023)	(0.00022)	(0.00022)	(0.00023)

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Community Bank × Property Damage	-10	0.000021	0.000031	0.000032	0.000027	0.000028	-0.00023
		(0.00063)	(0.00061)	(0.00062)	(0.00061)	(0.00063)	(0.00065)
	-9	0.000032	-0.0000018	0.000076	0.000069	0.000030	-0.000036
		(0.00065)	(0.00066)	(0.00065)	(0.00066)	(0.00064)	(0.00067)
	-8	0.00025	0.00068	0.00035	0.00032	0.00026	0.00017
		(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.00098)
	-7	-0.00051	-0.00048	-0.00053	-0.00055	-0.00049	-0.00065
		(0.00060)	(0.00063)	(0.00062)	(0.00062)	(0.00060)	(0.00061)
	-6	0.00034	0.00029	0.00032	0.00030	0.00035	0.00013
		(0.00038)	(0.00040)	(0.00038)	(0.00038)	(0.00038)	(0.00037)
	-5	0.00056	0.00051	0.00054	0.00053	0.00056	0.00046
		(0.00036)	(0.00038)	(0.00036)	(0.00036)	(0.00036)	(0.00037)
	-4	0.000062	0.00031	0.000087	0.000062	0.000070	-0.000013
		(0.00028)	(0.00027)	(0.00027)	(0.00027)	(0.00028)	(0.00032)
	-3	0.000090	-0.000094	0.000036	0.000043	0.000077	0.00011
		(0.00032)	(0.00038)	(0.00033)	(0.00033)	(0.00032)	(0.00033)
	-2	0.00022**	0.00022*	0.00024**	0.00023**	0.00022**	0.00032***
		(0.00011)	(0.00013)	(0.00011)	(0.00011)	(0.00011)	(0.00011)
	-1	0.000016	0.000045	0.000032	0.000022	0.000017	0.000095
		(0.00011)	(0.00010)	(0.00011)	(0.00011)	(0.00011)	(0.00012)
	0	0.00029	0.00057	0.00036	0.00030	0.00030	0.000063
		(0.00048)	(0.00046)	(0.00048)	(0.00049)	(0.00048)	(0.00048)
	+1	-0.000047	-0.00042	-0.000069	-0.000073	-0.000061	-0.00012
		(0.00075)	(0.00084)	(0.00076)	(0.00075)	(0.00075)	(0.00071)
	+2	0.00024	0.00023	0.00026	0.00025	0.00024	0.00031*
		(0.00019)	(0.00018)	(0.00018)	(0.00019)	(0.00018)	(0.00018)
	+3	-0.000041	-0.000015	-0.000022	-0.000030	-0.000040	0.000025
		(0.000070)	(0.000069)	(0.000077)	(0.000075)	(0.000072)	(0.000090)
	+4	0.0015***	0.0015***	0.0015***	0.0014***	0.0014***	0.0012***
		(0.00047)	(0.00046)	(0.00047)	(0.00047)	(0.00047)	(0.00044)
	+5	0.0016***	0.0013*	0.0016***	0.0016***	0.0016***	0.0015***
		(0.00059)	(0.00068)	(0.00061)	(0.00061)	(0.00059)	(0.00055)
	+6	-0.00031*	-0.00028	-0.00027	-0.00028	-0.00030*	-0.00020
		(0.00017)	(0.00023)	(0.00018)	(0.00018)	(0.00018)	(0.00017)
	+7	0.000058	0.000082	0.000076	0.000068	0.000056	0.00016
		(0.000092)	(0.00010)	(0.000088)	(0.000090)	(0.000089)	(0.00010)
	+8	0.00058	0.00055	0.00060	0.00056	0.00056	0.00039
		(0.00054)	(0.00046)	(0.00051)	(0.00054)	(0.00053)	(0.00044)
	+9	0.00046	0.00043	0.00048	0.00049	0.00043	0.00030
		(0.00072)	(0.00063)	(0.00072)	(0.00073)	(0.00071)	(0.00080)
	+10	0.000032	0.000035	0.000058	0.000048	0.000034	0.00014
		(0.00026)	(0.00031)	(0.00027)	(0.00026)	(0.00026)	(0.00027)
Year FE		Yes	No	Yes	Yes	Yes	Yes
Bank FE		No	No	No	No	No	Yes
County Controls		Yes	No	No	Yes	No	No
Bank Controls		Yes	No	No	No	Yes	Yes
Clusters		5,656	5,656	5,656	5,656	5,656	5,556
Observations		158,017	158,017	158,017	158,017	158,017	157,917
R^2		0.0263	0.000227	0.0224	0.0231	0.0259	0.0688
F-Stat		7.36***	1.758***	2.180***	3.358***	8.335***	5.523***

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period is 2003-2020.

Table A7: The Effect of Community Bank Status on Small Business Lending Growth: Robustness checks.

		(1)	(2)	(3)	(4)	(5)
Event Severity		Fatalities	Property Damage Per GDP	Property Damage Per Capita	Property Damage Per Capita	Property Damage Per Capita
Community Bank		0.033	0.014	-0.092	-0.091	-0.091
		(0.18)	(0.16)	(0.18)	(0.18)	(0.18)
Property Damage	-10	-64,251.9	2,826,159.0	0.000073	0.000071	0.000071
		(82,297.1)	(3,209,763.4)	(0.00078)	(0.00078)	(0.00078)
	-9	38,559.3	1,223,829.8	-0.00013	-0.00013	-0.00013
		(106,853.8)	(4,023,541.8)	(0.00064)	(0.00064)	(0.00064)
	-8	1,312.9	-1,561,075.1	-0.00031	-0.00031	-0.00031
		(88,946.7)	(7,808,848.4)	(0.0011)	(0.0011)	(0.0011)
	-7	66,233.8	3,508,913.0	0.00054	0.00054	0.00054
		(76,482.7)	(2,373,606.4)	(0.00061)	(0.00061)	(0.00061)
	-6	63,963.0	-3,900,371.2	-0.00050	-0.00050	-0.00050
		(82,467.0)	(3,568,654.5)	(0.00047)	(0.00047)	(0.00047)
	-5	-62,969.1	-1,012,852.6	-0.00044	-0.00044	-0.00044
		(78,906.4)	(2,242,469.7)	(0.00029)	(0.00029)	(0.00029)
	-4	60,439.0	337,077.6	-0.000026	-0.000026	-0.000026
		(72,520.9)	(1,525,154.0)	(0.00027)	(0.00027)	(0.00027)
	-3	-65,947.8	2,074,817.1	-0.000065	-0.000065	-0.000065
		(54,913.0)	(2,166,984.6)	(0.00033)	(0.00033)	(0.00033)
	-2	-7,554.4	-573,494.6	-0.00018***	-0.00018***	-0.00018***
		(15,441.9)	(367,826.6)	(0.000055)	(0.000055)	(0.000055)
	-1	29,795.3	404,270.9	0.000070	0.000070	0.000070
		(31,618.4)	(395,266.5)	(0.000079)	(0.000079)	(0.000079)
	0	-56,698.9	-8.09	-0.00016	-0.00017	-0.00017
		(46,495.7)	(23.3)	(0.00047)	(0.00047)	(0.00047)
	+1	-21,129.1*	-1,486,893.7	-0.00089*	-0.00089*	-0.00089*
		(11,538.5)	(4,322,407.7)	(0.00046)	(0.00046)	(0.00046)
	+2	6,303.3	-1,283,136.9***	-0.00025***	-0.00025***	-0.00025***
		(7,329.9)	(451,925.1)	(0.000096)	(0.000096)	(0.000096)
	+3	-118,691.9***	391,064.3	0.000064	0.000064	0.000064
		(30,817.1)	(320,690.1)	(0.000064)	(0.000064)	(0.000064)
	+4	9,071.0	-6,366,019.2*	-0.0012***	-0.0012***	-0.0012***
		(39,670.6)	(3,402,437.3)	(0.00045)	(0.00045)	(0.00045)
	+5	-20,752.5*	-11,065,276.6***	-0.0016**	-0.0016**	-0.0016**
		(11,855.5)	(3,486,803.9)	(0.00066)	(0.00066)	(0.00066)
	+6	12,811.7	-472,841.3	-0.00014*	-0.00014*	-0.00014*
		(9,778.1)	(972,566.2)	(0.000079)	(0.000079)	(0.000079)
	+7	53,226.7	-315,383.9	-0.000014	-0.000014	-0.000014
		(88,927.5)	(712,136.4)	(0.000084)	(0.000084)	(0.000084)
	+8	-44,643.8	-1,109,476.0	-0.00059	-0.00059	-0.00059
		(58,181.9)	(4,617,277.6)	(0.00051)	(0.00051)	(0.00051)
	+9	30,409.3	1,631,193.4	-0.00032	-0.00032	-0.00032
		(54,311.6)	(4,130,061.4)	(0.00072)	(0.00072)	(0.00072)
	+10	-64,251.9	-1,526,089.5**	-0.000088	-0.000089	-0.000089
		(82,297.1)	(632,410.3)	(0.00022)	(0.00022)	(0.00022)

Continued on next page

Community Bank × Property Damage	-10	59,515.9	-3,388,058.9	-0.00028	-0.00028	-0.00028
		(83,153.9)	(3,287,751.8)	(0.00079)	(0.00079)	(0.00079)
	-9	-52,802.0	-2,838,418.8	0.0000056	0.0000056	0.0000056
		(107,039.5)	(4,077,855.7)	(0.00065)	(0.00065)	(0.00065)
	-8	-6,358.8	1,570,176.6	0.00026	0.00027	0.00027
		(89,018.0)	(7,820,956.0)	(0.0011)	(0.0011)	(0.0011)
	-7	-72,312.4	-2,990,815.4	-0.00041	-0.00041	-0.00041
		(76,768.7)	(2,473,655.6)	(0.00062)	(0.00062)	(0.00062)
	-6	-69,913.8	4,141,744.8	0.00046	0.00046	0.00046
		(83,242.4)	(3,665,503.8)	(0.00049)	(0.00049)	(0.00049)
	-5	74,437.1	1,569,341.1	0.00051	0.00051	0.00051
		(79,996.7)	(2,538,130.0)	(0.00037)	(0.00037)	(0.00037)
	-4	-73,281.2	-281,643.1	-0.000055	-0.000055	-0.000055
		(72,652.3)	(1,750,227.5)	(0.00031)	(0.00031)	(0.00031)
	-3	67,804.2	-2,146,891.0	0.000022	0.000022	0.000022
		(55,115.7)	(2,283,161.3)	(0.00036)	(0.00036)	(0.00036)
	-2	6,529.5	1,169,312.8**	0.00025*	0.00025*	0.00025*
		(16,520.1)	(474,811.9)	(0.00014)	(0.00014)	(0.00014)
	-1	-27,138.5	-231,849.0	0.000074	0.000074	0.000074
		(31,878.4)	(418,887.9)	(0.00012)	(0.00012)	(0.00012)
	0	57,903.2	12.9	0.00027	0.00027	0.00027
		(46,784.6)	(23.9)	(0.00048)	(0.00048)	(0.00048)
	+1	22,898.2*	1,560,668.8	0.00070	0.00070	0.00070
		(13,699.8)	(4,380,095.7)	(0.00049)	(0.00049)	(0.00049)
	+2	-3,101.4	1,432,588.8	0.00033	0.00033	0.00033
		(8,126.3)	(908,615.2)	(0.00021)	(0.00021)	(0.00021)
	+3	115,717.0***	-310,015.8	-0.000027	-0.000027	-0.000027
		(31,089.9)	(358,841.0)	(0.000075)	(0.000075)	(0.000075)
	+4	-6,904.6	7,322,388.3**	0.0015***	0.0015***	0.0015***
		(39,912.6)	(3,630,237.6)	(0.00053)	(0.00053)	(0.00053)
	+5	5,548.1	12,175,039.6***	0.0019***	0.0019***	0.0019***
		(13,778.6)	(3,553,052.3)	(0.00069)	(0.00069)	(0.00069)
	+6	-11,870.4	-1,375,577.8	-0.00023	-0.00023	-0.00023
		(10,173.4)	(1,148,228.8)	(0.00016)	(0.00016)	(0.00016)
	+7	-56,636.6	386,504.8	0.000056	0.000056	0.000056
		(89,056.4)	(723,621.8)	(0.000090)	(0.000090)	(0.000090)
	+8	50,501.0	1,298,124.7	0.00066	0.00066	0.00066
		(58,657.7)	(4,667,816.1)	(0.00055)	(0.00055)	(0.00055)
	+9	-28,537.6	-430,519.7	0.00081	0.00081	0.00081
		(54,764.4)	(4,241,703.1)	(0.00078)	(0.00078)	(0.00078)
	+10	59,515.9	1,578,319.0	0.000013	0.000013	0.000013
		(83,153.9)	(1,011,326.9)	(0.00027)	(0.00027)	(0.00027)
State-Quarter FE		Yes	Yes	Yes	Yes	Yes
County Controls		Yes	Yes	Yes	Yes	Yes
Bank Controls		Yes	Yes	Yes	Yes	Yes
Method		OLS	OLS	OLS	PSM	PSM
Clusters		5,656	5,656	5,457	5,457	5,457
Observations		158,017	158,017	98,828	98,827	98,827
R^2		0.0263	0.0263	0.0311	0.0311	0.0311
F-Stat		7.436***	8.153***	5.406***	5.428***	5.428***

Notes: Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The sample period is 2003-2020.

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