STAFF
REPORTS

NO. 990
NOVEMBER 2021

How Bad Are Weather Disasters for Banks?

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FEDERAL RESERVE BANK *of* NEW YORK

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Federal Reserve Bank of New York Staff Reports, no. 990
November 2021
JEL classification: G21, H84

Abstract

Not very. We find that weather disasters over the last quarter century had insignificant or small effects on U.S. banks' performance. This stability seems endogenous rather than a mere reflection of federal aid. Disasters increase loan demand, which offsets losses and actually boosts profits at larger banks. Local banks tend to avoid mortgage lending where floods are more common than official flood maps would predict, suggesting that local knowledge may also mitigate disaster impacts.

Key words: hurricanes, wildfires, floods, climate change, weather disasters, FEMA, banks, financial stability, local knowledge

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1 Introduction

Policymakers around the globe are seriously considering the risks that climate change could pose to banks and the financial systems they anchor. Increasingly extreme weather is one possible channel (NASA (2005), Van Aalst (2006), Harvey (2018)). The destruction and economic disruptions caused by hurricanes, wildfires and other natural disasters may spillover to banks, particularly small, local banks square in the "eye" of the storm. If loan losses spike, or if customers move away over the longer run, bank solvency could be threatened. Indeed, the banking panic of 1907 was triggered by the earthquake and fire that ravaged San Francisco in 1906 (Odell and Weidenmier, 2005).

We size up this disaster channel by studying how banks fared against disasters past. We study FEMA-level disasters over 1995-2018 and county-level property damage estimates from SHELDUS (Spatial Hazard Events and Losses Database for the United States). Bank exposure to damages in a county is proxied by its branch presence there. We look at hyper-local banks operating in just one county and at more diversified banks operating across multiple counties. We estimate regression models relating disaster exposure to standard bank performance and stability measures - loan losses, income, return on assets, capital strength, and default risk (Z-score) over the short and medium run (up to five-years). To account for correlations in areas prone to disasters and bank performance, we saturate the models with fixed effects and control for time-varying county characteristics.

When we consider all FEMA disasters, we find generally insignificant or small effects on bank performance and stability. In particular, loan losses and default risk at local banks do not increase significantly. Charge-offs at multi-county banks increase but the impact is very small. Moreover, not all effects are bad; income of multi-county banks increase significantly with disaster exposure.

Extreme weather is expected to become more extreme as the globe warms, so we also look separately at the most damaging (90th percentile) of disasters. We again find that losses at larger (multi-county) banks are barely affected and their income increases significantly with exposure. For local banks, we do find more negative stability effects from extreme disasters. However, even these are not sufficiently large to threaten bank solvency. In part this may be due to offsetting effects. Local banks' income also increases after these more severe disasters.

The modest effects we find may be surprising, so we explore three factors that might account for banks' resilience. The first and most obvious candidate is FEMA disaster aid. That aid, which can be substantially, primarily flows to households to help cover uninsured losses but it could buttress banks indirectly by supporting borrowers and the local economy. FEMA aid to individuals and households by county is not public, so we investigate any mitigating effects indirectly using two strategies. In the first, we expand our disaster set to include destructive weather events that did not trigger a FEMA declaration and compare the impact of such ordinary disasters to those of FEMA disasters. We find that, for given damages, non-FEMA disasters are not notably worse for local banks, suggesting FEMA aid does not explain their resilience. We find similar results in the second test where we exploit discontinuities in FEMA declaration coverage (for a given disaster) along state borders.

A second, endogenous, factor that might mitigate disaster effects on banks is increased demand for loans. Households and businesses may need credit for rebuilding or to smooth out temporary income disruptions. In addition to alleviate the disaster impacts on borrowers, new "recovery" lending may help offset losses on loans already on the books. Consistent with that premise, we find that lending increases significantly after disasters, though only at multi-county banks.

Local knowledge is a third possible mitigating factor. Banks located closer to their borrowers have been found to harbor knowledge of both borrowers and local risk that more distant lenders may lack. We extend that idea by investigating if local banks superior geographic knowledge helps them avoid areas where disaster risks are more frequent than expected based on common knowledge. To that end, we digitize all FEMA flood zone risk maps for 2019 and merge them with HMDA (Home Mortgage Disclosure Act) data. We find that local banks reallocate mortgage lending from census tracts where flood risks seem understated relative to the FEMA maps (given recent flooding experience). We do not observe such behavior at multi-county banks.

Our main findings are generally consistent with the few papers that study the bank stability effects of disaster. Looking across countries, Klomp (2014) finds that disasters do not effect default risk of banks in developed countries. Brei et al. (2019) find that hurricanes (the most destructive weather disaster) do not significantly weaken Caribbean banks. Koetter et al. (2019) finds increased lending and profits at German banks exposed to flooding along the Elbe River. The study closest to ours by Noth and Schuewer (2018) finds default risk increases at U.S. banks following disasters but the effects are small and short-lived. Barth et al. (2019) find higher profits and interest spreads at U.S. banks after disasters but did not look at bank risk. Based on four case studies of extreme disasters and small banks, FDIC (2005) concluded that ..."historically, natural disasters did not appear to have a significant negative impact on bank performance." Our paper extends this literature three ways: we study more bank outcomes, both income and balance sheet, we pay special attention to undiversified local banks, and we explore why banks' seem so disaster resilient.

Our findings also relate to recent research on how weather disasters affect bank lending. Chavaz (2016) shows that banks increased lending in response the severe hurricanes in 2005. Cortes and Strahan (2017) and Ivanov et al. (2019) show how bank holding companies accommodate increased mortgage and business loan demand after disasters using their diversified holding company structure. Berg and Schrader (2012) finds that bank relationships tend to improve credit access following volcanic eruptions. These papers did not look at the bank stability effects of disasters. More generally we contribute to the emerging climate-finance literature. Hong et al. (2019) and Bernstein et al. (2018) show that long run sea level rise may have already been priced into coastal properties, driven by sophisticated buyers. Baldauf et al. (2020) find salience effects of climate risk pricing; home prices reflect flood risk more significantly in neighbourhoods where residents believe in climate change. Muller and Hopkins (2019) show that current flood risks affect real prices; they make use of salience arguments to disentangle risks from actual damage. Engle et al. (2019) show how climate change news and corporate environmental scores can be used to hedge against climate change news "shocks." Painter (2018) find that counties more exposed to sea level risk pay higher underwriting fees for bonds. Krueger et al. (2020) find that climate risks - especially those related to regulatory changes - are already materializing in portfolios. Vigdor (2008) discusses the flooding of New Orleans after hurricane Katrina and the long term economic viability of such coastal cities based on reclaimed land. Strobl (2011) shows that hurricanes depress GDP in a community, in part by out-migration.

In the policy sphere, we contribute to ongoing efforts by regulators and researchers trying to resolve how banks and financial systems will hold up against climate change. Our findings suggest that the acute, physical risks to banks are not first-order. Bank's resilience against such risk should reinforce the financial system more broadly. More chronic physical risks and transition risks may warrant more focus (Batten et al., 2016).

The next section describes our data and regression model. Section III presents the main findings and robustness tests. Section IV explores three possible mitigating factors that might explain banks' disaster resilience– FEMA aid, increased loan demand, and local knowledge. Section V concludes.

2 Data and Regression Model

2.1 Disaster Data

We study FEMA disasters, weather events sufficiently destructive to a state that its Governor formally requests federal assistance from the President. Most request are granted, so we have thousands to study since the mid-90s. Some are denied, a fact we use later. If the request is granted, the official declaration to that effect releases significant financial aid to individuals and households facing uninsured losses in the stricken area. Basic details on all FEMA disaster declarations – date, type, counties – are on its website.

FEMA does not report damage estimates, so we use SHELDUS[1] SHELDUS estimates damages for every U.S. weather event that causes property or structural damage. These damages are estimated based on reports from insurers and local weather stations. While commonly used in research, there are known measurement errors (Roth Tran and Wilson, 2020).[2] Differences in how damages are estimated are typically affected by the institutions that measure them, which follow state lines. This can be accounted for to some extent in our regression framework (see below).

[Figure 1 about here]

Figure 1 shows how FEMA weather disasters tend to cluster geographically. Naturally, "disasters" are clustered into populated regions, primarily along the coast as well as in the center of the country along larger waterways. We differentiate between floods that are not associated with a storm, storms, and hurricanes (subsuming both the related floods and wind events). The Figures show that hurricanes primarily strike the south-east of the US while non-hurricane storms are more likely to strike the mid-west. Floods, which are not associated with hurricanes, are concentrated around large waterways, the Mississippi basin in particular.

Note the obvious discontinuities in FEMA disaster coverage along some state borders e.g. New York and Pennsylvania. We exploit those breaks later to identify the effects of FEMA financial assistance. While damages are supposed to drive disaster declarations, political forces also come into play.[3] For instance, Gasper (2015) finds that Presidents are less likely to declare disasters, for given damages, in

[1] SHELDUS was developed at the University of South Carolina. Since 2018, the Arizona State University and the department of Homeland Security have maintained it.

[2] This is corroborated in direct discussions with SHELDUS data managers.

[3] Former FEMA director James Witt: "...disasters are very political events" quoted in Sobel and Leeson (2006).

non-election years. However, in our main specification we include state-by-year and disaster type-by-state fixed effects that help control for electoral cycles' effects as well as any differences in the propensity for states to seek disaster aid for certain types of events. Consider, for instance, that Alaska and Arizona record nearly the same number of winter-weather related disasters.

[Table 1 about here]

Table 1 summarizes FEMA incidence and damage estimates from SHELDUS.[4] Floods, windstorms, and thunderstorms are the most frequent disasters but hurricanes, wildfires, and landslides are the most destructive. Hurricanes, for instance, each cause over 32 million USD in damages on average. Floods, the fourth most destructive, cause about 7 million USD worth of property damages in an average event. The worst losses (90th percentile) of severe disasters still show significant heterogeneity; they range from 12 million USD for floods to 130 million USD per county for hurricanes.

2.2 Bank Data

We collect bank data from their quarterly "Call Reports" to their federal regulators (FR Y-9C and FFIEC 002). They are publicly available from the Federal Reserve. We study loan charge off rates, net income, net income per assets (ROA), ROA volatility, capital ratios, and Z-scores, a (inverse) measure of default risk. [5] We annualize the data by averaging across quarters each year. Our data spans 1995 to 2018.

For most analyses, we study banks with all branches in a single county separately from multi-county banks [6]. Despite consolidation, single-county banks are still numerous in the U.S., accounting for over 40 percent of our sample, and their geographic concentration leaves them acutely exposed to weather disasters in their county. By contrast, a multi-county bank facing a disaster in one county may better weather the storm by drawing on liquidity and capital from non-affected counties. Some single-county banks become multi-county banks over the sample (or are bought), so to avoid selection effects we exclude those bank-years from the five-year horizon we use when estimating disaster effects (see below).

A bank's exposure to a disaster in a given county is measured by the extent of damages, weighted by a bank's branch presence in the county relative to its own branch network as well as the density of other banks in the county (this follows Cortes and Strahan (2017)):

[4] We exclude FEMA disasters with zero SHELDUS damages and non-weather disasters (volcanoes and earthquakes)

[5] Z equals the sum of capital/asset and RoA divided by the standard deviation of ROA over the prior five years.

[6] The FDIC Summary of Deposits identifies bank branch location

$$Exposure_{b,c,t} = ln[Damages_{c,t} * \frac{b\,branches\,in\,c}{branches\,in\,c}] * \frac{b\,branches\,in\,c}{b\,branches} \quad (1)$$

The distribution of damages is skewed rightward far more than normally (long thin tails) so converting to logs is appropriate for estimating average disaster effects. We consider extreme disasters with "unlogged" damages later. The first weight on damages is the number of bank b's branches in c divided by the number of all branches in c. That effectively distributes damages in county *c* in proportion to each bank's share of the market there. The second weight captures the importance of county c to bank b's overall business. This equals one for single-county banks.[7]

[Table 2 about here]

Table 2We study public, federal regulatory data reported over 1995-2018 at the bank x year level. These data provide a reliable view into banks' business, prospects, and stability. They are workhorses for bank supervisors and researchers. After dividing banks by branch footprint we have about 36,000 single-county bank observations and 51,000 multi-county (i.e. banks with branches in more than one county) bank observations .

Table 2 provides sample statistics. As can be seen, our measure of relative disaster exposure is lower, on average, at single county banks (0.83 v. 1.17), but their assets are only one-tenth as large as those of multi-county banks, reflecting the larger relative impact individual disasters can have on banks. However, median exposure for any bank in a given year is for 0, as idsasters are still relatively rare occurrences. The remaining rows of the table summarize the bank outcomes we study. We look first at the performance and risk measures - loan charge-off rates, income (in logs), ROA, ROA volatility (SD(ROA), and Z, a (inverse) default risk measure. Note that Z and SD(ROA) are calculated based on five-year moving average of quarterly data. We also look at how disasters affect bank lending, total lending and by major category. [8]

[7]Given equal branches, damages to banks located primarily in urban counties with dense banking markets may be attenuated relative to regional and small banks. We control for county population and bank competition to account for that.

[8]Return on Assets (ROA) appears low (compared to the customary 1 percent) because we have averaged quarterly observations.

2.3 Regression Model

Weather disasters might negatively affect banks in several ways. Economic disruptions to their customers or uninsured property losses could spillover to banks via higher loan losses with knock on effects to bank income and capital. If the local economy contracts or property values depreciate permanently, bank health would be expected to decline as well. Offsetting effects are also possible. Beyond the two already mentioned - federal disaster aid and recovery lending - insurance is a third likely stabilizer. Homeowners' insurance against weather disasters protects lenders' as well. However, due to a lack of data we do not consider insurance coverage across counties. If coverage correlate positively with disaster exposure our impact estimates could be biased downwards. County fixed effects and time varying county income controls attenuate possible bias in cross county insurance differences to some extent. However, the baseline effect of insurance remains an unobservable concern.

We estimate any direct disaster exposure effects by regressing bank outcomes on disaster exposure using bank x county x year panel data:

$$Y_{b,c,t} = \alpha + \sum_{i=0}^{5} \beta_i Exposure_{b,c,t-i} + \delta C_{b,c,t} + \alpha_b + \omega_{s,t} + \chi_{s,d-type} + \epsilon_{b,c,t} \tag{2}$$

The β coefficients measure how performance varies with exposure. Our identifying assumption is that bank performance does not influence exposure, including through bank location choices. This assumption is reasonable in the short- and medium-term. To capture short- and medium-term impacts we include five lags of exposure. Exposure does not vary much over time so the coefficients on lagged exposure captures delayed effects. To isolate the effect of specific disasters, we control for any other disasters occurring within the five-year observation window separately (as in Roth Tran and Wilson (2020)) .

We control for bank size (assets), whether the bank is part of a holding company, bank deposit concentration (the HHI), and county characteristics (income, population, and race) from the Census. We include fixed effects for the bank to control for differences in business models and the state-year fixed effects to control for state business cycles. For single-county banks we include a county fixed effects to absorb county-specific risks that might affect bank performance. Standard errors are clustered by county for single county banks. Spatial clustering is less obvious for multi-county banks so we use Newey-West standard errors.[9]

[9] Our results are robust to using Newey-West clustering throughout.

3 Results

3.1 Baseline: All FEMA disasters

Table 3 reports the exposure coefficients for regression (2) in the year following the disaster and the sum of coefficients at the 3 and 5 year horizons. To help gauge magnitudes, the bottom row reports a scaled cummulative five-year impact: the sum of coefficients (over 5-years) times the standard deviation in exposure divided by the outcome mean (in percent). The "all bank" sample includes single and multi-county banks as well as banks that transition from one group to the other (or drop) during the observation window.

[Table 3 about here]

We find insignificant or modest effects of disaster damages on bank outcomes. For single-county banks, the estimates for charge-offs, capital, ROA volatility, and Z scores are small and insignificant. Net income and ROA decline at single-county banks with disaster exposure but the effect is only marginally significant and small, as shown on the bottom row. A standard deviation increase in disaster exposure reduces ROA by about 3 percent relative to mean ROA at the five year horizon. Charge-offs rise a little over two percent though the effect is insignificant. For multi-county banks we observe a delayed increase in charge-off rates five years after a disaster by about 10 percent relative to average. However, the baseline charge-off rate is so low that this increase is not destabilizing. In fact, multi-county banks' net income increases significantly, if slightly, with exposure, consistent with Barth et al. (2019).Higher income post disaster suggests that asset growth explains lower ROA (income/assets). Z -scores at multi-county banks also increases with exposure in the year of the disaster – implying a greater distance to default –, evidently reflecting higher net income. Results for all bank are reported in panel C. Charge-offs increase by about 9 percent a few years after the disaster, mirroring the effect for multi-county banks. All other effects are not statistically or economically meaningful.

To provide a more dynamic perspective, Figure 2plots coefficient estimates each year for three outcomes: net income, charge-offs, and Z-score. The vertical axis measures the impact of a standard deviation increase in exposure on each as a percentage of the mean of the outcome over the sub-sample. For single-county banks we observe the same delayed increase in chargeoffs for single and multi-county banks, although the effects for the former are insignificant. Z-score for those banks increases initially, then declines modestly over the horizon.

[Figure 2 about here]

Overall, these results suggest disaster exposure may increase credit losses, with a delay, by as much as ten percent relative to average. An increase of that magnitude is surely important from a bank internal risk management perspective, given low aggregate baseline charge-off rates, however, it is less clear that it rises to the level of systemic risk. Moreover, stability measures such as capital ratios, default risk, and income are unaffected or increase slightly after disasters.

3.2 Extreme Disasters

The results above suggest that the average FEMA disaster is not detrimental to bank stability. This section looks at the impact of more extreme disasters, with damages in the 90th percentile. This is important because distribution of damages has a long right tail; for example, hurricanes in the 90th percentile are 500 times more destructive than hurricanes in the 10th percentile. We limit our sample to the top 10 percent of all disasters and measure a bank's exposure as above, except we use "unlogged" damages. Studying the 90th percentile and unlogged damages poses a severe stress test of bank resilience. We set the value of all FEMA events below the 90th percentile of damages to zero and merely track their occurrence (as a binary measure) in our controls.

[Table 4 and Figure 3 about here]

Table 4 reports the cummulative results, as above. For coefficient legibility, we scale disaster damages by 10 million USD. Figure 3 shows standardized scaled coefficients for a given year. Here we find more significant effects from extreme disasters on single-county banks. Charge-offs increase significantly for a few years, but the cumulative effect is less than five percent relative to average. Income increases as does income (ROA) volatility. The most pronounced effect is the decline in Z score, which likely reflects increased ROA volatility (since ROA and capital ratios are not affected beyond one year). A standard deviation increase in exposure to extreme disaster damages reduce Z-scores at single-county banks about 9 percent relative to average. For comparison, the average Z-score of banks dropped by over one third (>33%) during the great recession. The results for multi-county banks are similar to before except (curiously) we do not observe increased charge-off rates after extreme disasters. Importantly, we still observe higher income and also higher RoA.

In sum, we find modest, positive income effects of disasters but few balance-sheet effects. Loan losses may increase but not to destabilizing levels. In no case do we see declining capital ratios due to disasters. Multi-county banks seem to profit from even extreme disaster exposure. Extreme disasters are somewhat worse for single-county banks than average disasters, but the effects do not seem destabilizing, particularly as profits rise somewhat.

4 Mitigated Disasters?

The above results beg the question of why weather disasters are not harder on banks. In this section we investigate three factors that might mitigate their impact: federal disaster aid, increased loan demand, and local bank knowledge.

4.1 Disaster Aid

FEMA declarations trigger a substantial flow of federal financial assistance to stricken counties to help cover uninsured losses to households. The aid may help households stay current on debts to banks and can, more generally, sustain the local economy. This section investigates if FEMA aid explains banks' resilience to disasters using two strategies. Unfortunately, we cannot control for FEMA aid directly for a number of reasons the most important of which is that direct aid to households is poorly recorded for past disasters.[10] We test the proposition in two ways, both of which exploit possible political effects in FEMA declarations.

For the first test we consider all disasters recorded in SHELDUS and compare events that received a FEMA declaration to disasters with comparable damages that were not, for whatever reason, declared a FEMA disaster. Assuming the reasons for a declaration (or lack thereof) are exogenous to individual banks (especially local single-county banks), we can identify the FEMA effect by using non-FEMA disasters as the control group. Our bank-level exposure measure is defined as described in (1) above. There are a sizable number of non-FEMA disasters with comparable damages to FEMA disasters, as seen in Appendix fig. A.1. We therefore estimate a modified version of the regression model that allows for FEMA effects:

$$\begin{aligned} Y_{b,c,t} =& \alpha + \sum_{i=0}^{5} \beta_i Exposure_{b,c,t-i} + \gamma FEMA_{c,t} + \sum_{i=0}^{5} \nu_i FEMA_{c,t} * Exposure_{b,c,t-i} + \\ &+ \delta C_{b,c,t} + \alpha_b + \omega_{s,t} + \chi_{s,d-type} + \epsilon_{b,c,t} \end{aligned} \tag{3}$$

[10] Payouts can go to individuals or institutions – including the state governments, which can dole out funds to affected households and businesses. Even if payouts are publicly announced, it is often unclear which counties receive actual funds. A cleaner test of the benefit of FEMA funds is a 0/1 comparison of similar regions.

The FEMA indicator equals one for FEMA disasters, and zero for other disasters. The coefficient on the interaction term measures any mitigating effect of a FEMA declaration on disaster exposure.

[Table 5 about here]

The estimates are reported in Table 5. For simplicity and ease of identification, we focus only on single-county banks. The top panel reports the effects of bank exposure to (unmitigated) non-FEMA disasters. The only notable difference from the FEMA disaster estimates reported earlier is a significant, but small, increase in ROA volatility. The bottom panel reports the effects of bank exposure to disaster damages interacted with a dummy denoting a FEMA disaster. Those results are somewhat mixed; charge-offs decline significantly after FEMA disasters, suggesting FEMA aid to households may help support banks in turn. However ROA also tends to decline after FEMA disasters. On the whole, these results do not suggest that the muted effects we found earlier are due to FEMA declarations. That is, even non-FEMA disasters do not induce balance sheet contractions or increase losses among affected banks. We confirm, this in Appendix Table A.2, in which we restrict our sample to events with the highest overlap in recorded damages. As such, we ensure that neither small events nor extremely large outlier events drive our results.

The second test exploits the discontinuities in FEMA declaration along state borders noted earlier. We restrict our sample to border counties that sustain damages from a given disaster, then compare outcomes in counties that were covered by a FEMA declaration to those that were not. FEMA declarations are known to be driven partly by political factors as well as the extent of damages, and the obvious discontinuities along state borders attest to this. Severe disasters near a state border can cause significant damages in counties on both sides, but due to political frictions (or aggregate damages falling more heavily on one state), only one governor asks for or receives a FEMA declaration. We estimate the FEMA effect by interacting bank exposure, as measured above, with a FEMA indicator equal to one if a county sustaining damages from a given disaster was covered by a FEMA declaration (and thus eligible for aid) and zero otherwise. We limit our sample to local banks operating in contiguous counties of separate states, which were affected by the same disaster that was declared a FEMA event in some states but not in others. As above, given damage exposure and the FEMA indicator, the coefficient on that interaction measures the mitigating effect of aid triggered by a FEMA declaration for the same disaster.

[Table 6 about here]

Table 6 reports the results. As stated, we again focus on the hyper exposed local banks for this analysis. We still find largely null effects of disasters. The slight negative reaction of charge-offs in ordinary disasters may be related to bank's being able to account for loan delinquencies more generously after a disaster event. Importantly, we do not find that FEMA declarations are drivers in mitigating otherwise severely negative events for banks.

4.2 Increased Loan Demand

Households and businesses alike may demand more credit after disasters, whether for rebuilding or consumption smoothing. Several studies, cited earlier, find increased bank lending of one type or another following disasters. Indeed, some identify disasters as loan demand shocks in order to study the supply response of banks and other lenders (Cortes and Strahan, 2017). Our question in this section is whether increased lending after disasters helps explain why banks seem relatively unscathed by disasters. Do earnings on new loans help mitigate losses on old loans? To investigate that proposition, we estimate model using bank loans as the dependent variable. We consider total loans and the major loan components: residential mortgages, commercial and industrial (C&I) lending, and consumer lending.

[Table 7 about here]

As shown in the bottom panel of Table 7, total bank loans increases significantly following disasters, reflecting increased demand across the board: mortgage, business, and consumer. This reinforces other recent findings and extends it to small business lending, which is less studied in the context of climate literature. Also new is that that the "all bank" response is driven entirely by multi-county banks; loans at local banks are not significantly affected by disasters. This bifurcated response is consistent with recent findings that bigger banks are better able to fund recovery lending by siphoning financial resources from unaffected counties where loan demand is (relatively) weak. Interestingly, the loan response tends to increase with the horizon. A standard deviation increase in disaster exposure increases total loans at multi-county banks after five years by 0.26% relative to average. The small business loan response is relatively large, even at small banks (though not statistically significant)

A natural question is whether banks raise loan rates in response to increased demand or heightened risk after disasters. Banks do not report loan rates in their Call Reports, but the ratio of total interest income to total loans can proxy for average rates. The final column shows that average interest

("Int./Loans) does not increase post-disaster and if anything, tends to fall.

4.3 Local Knowledge

The benign effects of disasters on local banks might reflect a possible information advantage that helps them steer clear of flood-prone areas within a county.[11] We find some evidence for that proposition using borrower-by-lender-by-location mortgage data. For this analysis, we digitize recent FEMA flood zone maps and project these to the census tract level. We find that all lenders avoid high risk (100-year flood) hazard zones, but local banks more so. We find an even starker differential where potentially outdated FEMA flood maps may understate actual flood risks.

The Home Mortgage Disclosure Act (HMDA) data we use covers virtually all mortgage applications, accepted or not, in U.S. Data available to the Federal Reserve System allowing us to pinpoint the location – usually at least the census tract – of any application. We define local lenders as those with over half of their (cumulative) mortgage lending to borrowers in a single county (we include all lenders for this analysis, including non-banks). Our sample period covers 2005 to 2018.

We digitize 2019 FEMA flood maps to identify high flood risk zones within counties. An example, for lower Manhattan, is shown in Appendix Figure A.2. The maps delineate areas expected to suffer serious or catastrophic flooding once every 100 (or 500) years. [12]. We digitize 2019 FEMA maps then project across census tracts. Many tracts are either entirely in or outside of a flood zone. For tracts that are only x% in a flood zone, we assume a x% flood zone risk for all mortgage applications in that tract. Since a tract usually contains between 1000 and 8000 individuals, these are frequently very small geographic areas. This is especially true in and around major cities, which often line the coast or large waterways that are also most liable to flood.

Even with mandatory flood insurance in high risk zones, lending there can be hazardous. For one, flood insurance is naturally costlier in hazard zones, so insurance payments can strain borrowers' ability to make mortgage payments. Insurance markets are also incomplete, so uninsured losses are possible. Finally, non-property losses from floods due to economic disruptions, job loss, or property abandonment can spillover to lenders.

[Table 8 about here]

[11] Dlugosz et al. (2021) find that local knowledge, as proxied by branch managers' discretion to price deposits, amplifies the mortgage lending response to disasters.

[12] We account for 500 year flood zones separately in the controls to ensure these do not influence our results. We exclude any actual waterways, seas or otherwise uninhabitable areas from our analysis

To investigate if local banks heed flood risks more than others, we regress an indicator of whether a given application is accepted on a flood zone share at the census tract level, local bank indicator, and their product.

$$
\begin{aligned}
Y_{i,b,l,t,c} =& \alpha + \beta_1 FloodZone_c + \beta_2 LocalBank_{b,l} + \beta_3 FloodZone_c * LocalBank_l + \\
& \Omega_l + \gamma_i + \pi_t + \epsilon_{i,b,l,t,c}
\end{aligned}
\tag{4}
$$

The coefficient of interest is β_3; the interaction between the dummy variable Local bank, which denotes whether lender b is local to county l, and the share of the census tract that is a 100 year flood-zone. The coefficient on the product measures any differential response of local lenders to flood risk. The regression includes controls for individual borrower i (including sex, race, income, dual applicant status), county/location fixed affects and time-varying characteristics l (ethnic makeup, mean income), bank characteristics b (whether a lender is local, lender type, lender size), a time fixed effect and – finally – the share of the census tract c that is designated a flood zone.

Table 8 reports the estimates. Column (1) shows that lenders generally are more likely to deny a mortgage application in 100 year flood zones, but local banks especially so. On average, a loan application has a 1.3% points lower chance of being accepted in a flood zone, but this rises to 2.3% points if the bank is local to the area. This result is unaffected if we include a triple interaction that accounts for bank-type (not reported for brevity).

Columns (2) and (3) report regressions where the dependent variable is the mortgage amount, in logs, conditional on acceptance. Studying that outcome guards against "discouraged borrower" bias; where prospective applicants, anticipating rejection after talking to a mortgage broker, do not bother to apply. Given borrower income and other controls, mortgages by local banks in flood zones are 8.5% smaller than mortgages by non-local lenders (Col. 2). The difference-in-difference is almost 11% when we include interactions of bank-type with the share of the census tract that is a flood zone (Col. 3). Collectively, these results suggest that local banks are more cautious flood zone lenders along the intensive (approve/deny) and extensive (loan amount) margins.

Local lenders' aversion to flood zones might merely reflect higher risk aversion rather than superior knowledge. After all, FEMA flood maps are readily available to all lenders, local or otherwise. Where local knowledge may come into play is when flood maps are inaccurate or outdated, as they can be

[13]. Indeed, rising sea levels and increasing extreme weather driven by climate change almost dictate obsolescence. Development can also change flood risks by changing draining patterns. To that point, Houston suffered 3 "500 year" floods in three years.[14]

To see if local banks are better informed about risks not captured by flood maps, we split the sample based on actual flooding history since 1960: "Low risk" areas have experienced less than 3 floods; "high risk areas" have experienced more than 5 FEMA floods. We then re-estimate the regressions above that use loan amounts as the dependent variable for each sample.

[Table 9 about here]

Table 9 reports the results. The coefficients on *Local bank x 100-Year Flood zone* are significantly negative in both low and high risk zones, as before, the estimate for high risk areas is substantially larger (Col (1) and (3)). However, local bank mortgages are 29% smaller in census tracts that are truly high risk vs 5% smaller in regions that are relatively low risk. Columns (2) and (4) show the differential effect is robust to allow interactions between all lender types and FEMA flood zones.

These results support the proposition that local banks' better knowledge of the "lay of the land," beyond common knowledge from FEMA maps, that mitigates their exposure to disastrous floods. Floods are the most frequent type of disaster, so this helps explain our main result showing that local banks are largely unscathed by disasters generally.[15]

5 Conclusion

More extreme weather is one potential vector from climate change to bank and financial stability. It is a standard, prominent arrow in diagrams showing potential transmission mechanisms. Our findings suggest the disaster channel is not likely a material source of instability for banks. Even very small banks facing extreme disasters are not substantially threatened.

This resilience seems inherent to some degree because disasters increase the demand for loans. Earnings on new loans helps offset losses on loans on the books. In fact, income for larger banks increase after disasters. Local banks also manage to limit exposure to high risk areas, perhaps reflecting

[13] See for instance Thomas (2020): "Studies Sound Alarm on "Badly Out-of-Date" FEMA Flood Maps" in Scientific American

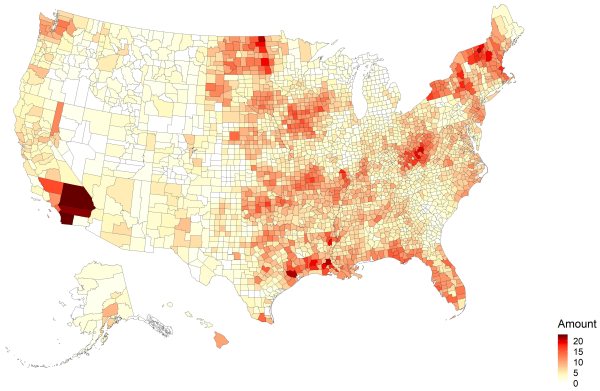
[14] https://www.washingtonpost.com/news/wonk/wp/2017/08/29/houston-is-experiencing-its-third-500-year-flood-in-3-years-how-is-that-possible/

[15] Banks also mitigate weather risk by selling (securitizing) mortgages to government sponsored enterprises. Ouazad and Klam (2019) find that securitization activity increases after billion-dollar disasters.

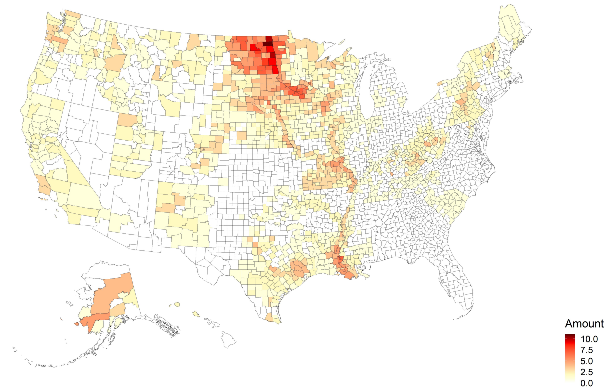
their greater knowledge of such risks. Those endogenous factors seem to buttress banks more than federal disaster assistance. Insurance is another likely mitigating factor that we do not explore. That is worthwhile topic future research.

For policymakers, our findings suggest that potential transition risks from climate change warrant more attention than physical disaster risks.

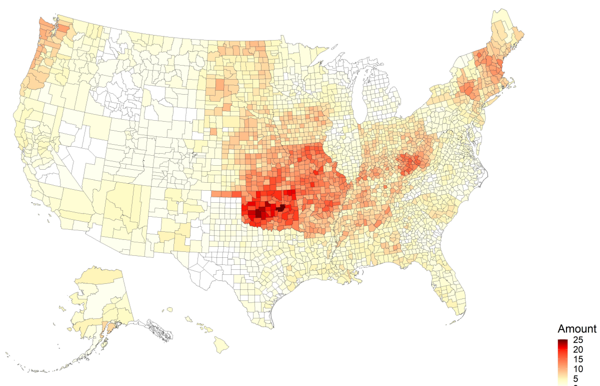
Cumulative FEMA Disaster Events by County and Type: 1995 - 2018



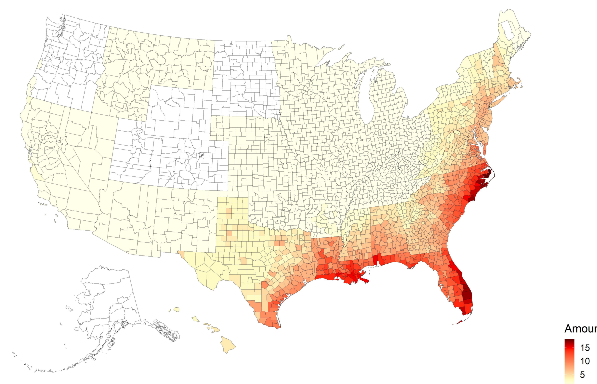
(a) *All FEMA events with non-zero damage*



(b) *Floods (non-hurricane)*



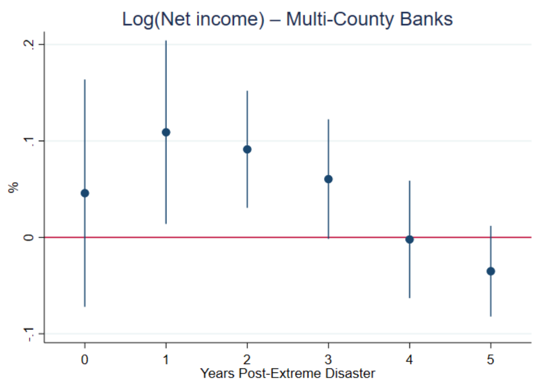
(c) *Storm*



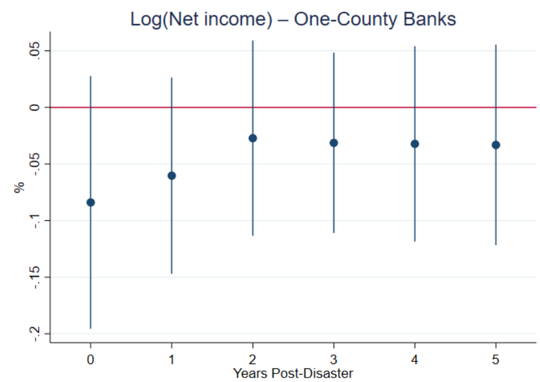
(d) *Hurricane*

Figure 1: *Note: This figure shows the number of FEMA events that have occurred in counties across the US. Panel (a) shows all FEMA events with non-zero damages. Panel (b) shows (non-hurricane) flooding. Panel (c) shows storm events. Panel (d) shows hurricanes.*

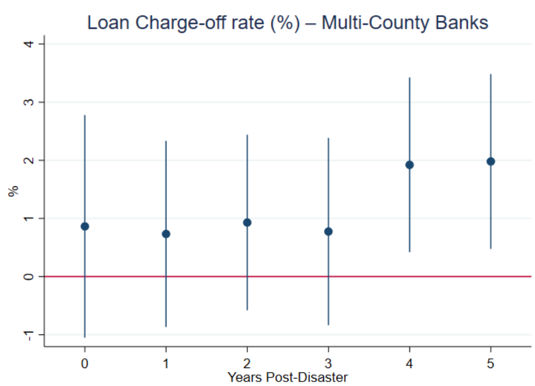
Figure 2. Impact of Disasters on Bank Income, Charge-offs, and Z scores



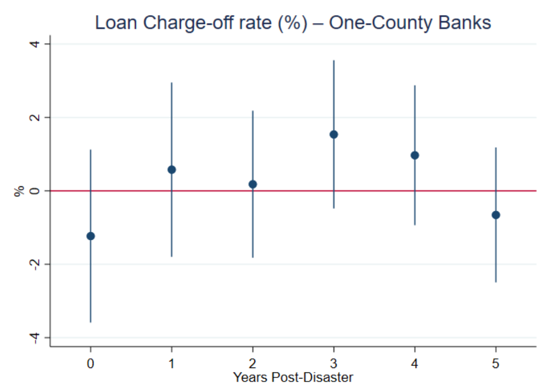
(a)



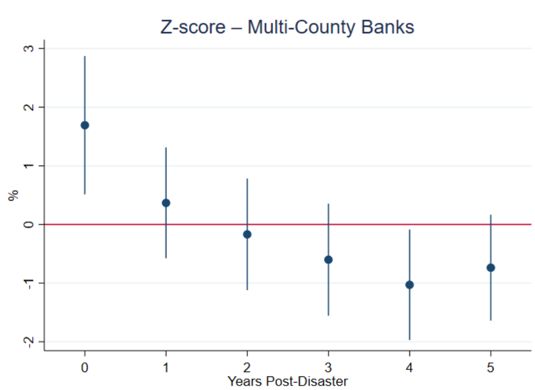
(b)



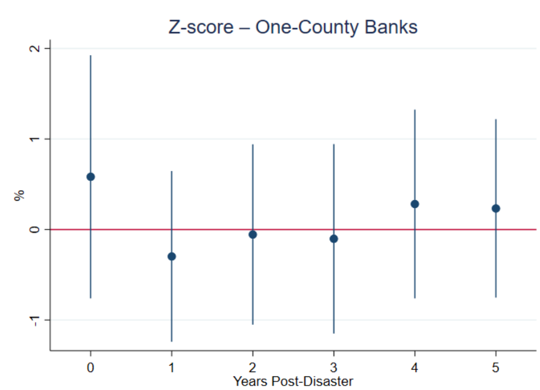
(c)



(d)



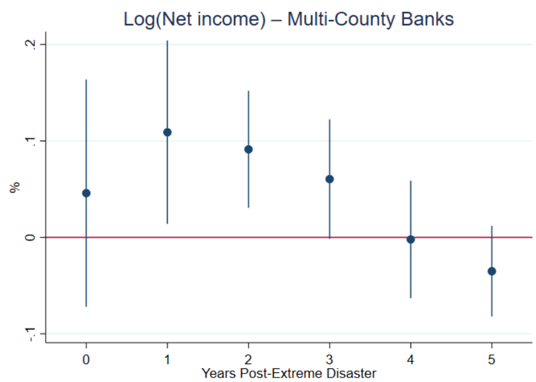
(e)



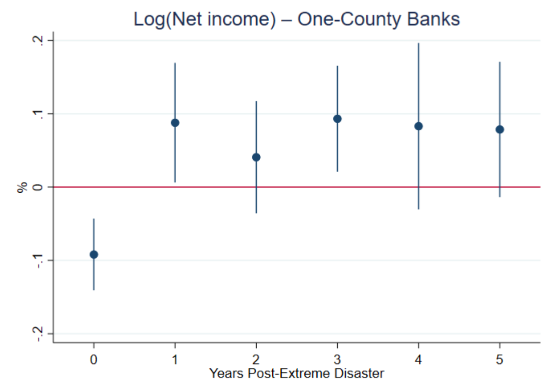
(f)

Figure 2: ***Note*** *This figure plots the scaled individual (non cumulative) coefficients and 95% confidence bands of our primary specification for the outcomes and bank type indicated. Coefficients are scaled to represent a one-standard deviation increase in disaster exposure on the outcome variable, relative to the unconditional full sample mean. They can be read as percent changes of the dependent variable.*

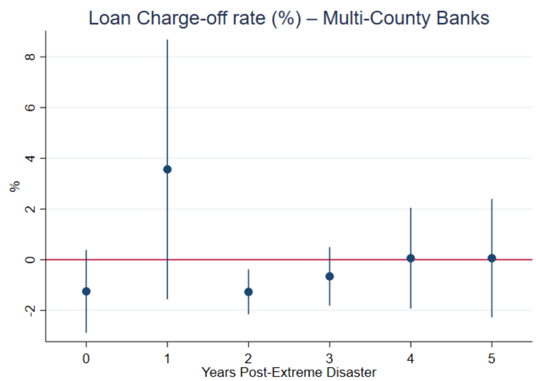
Figure 3. Impact of Severe Disasters on Bank Income, Charge-offs, and Z scores



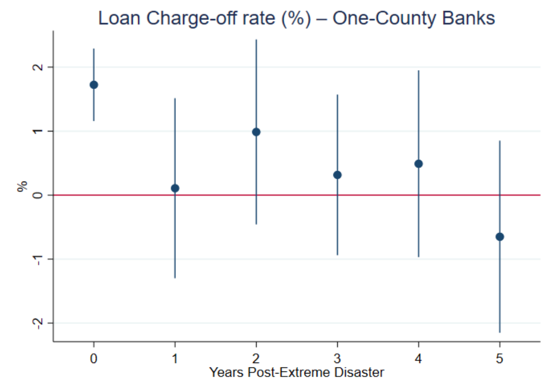
(a)



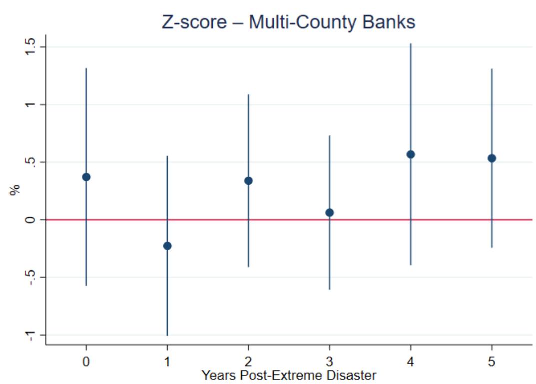
(b)



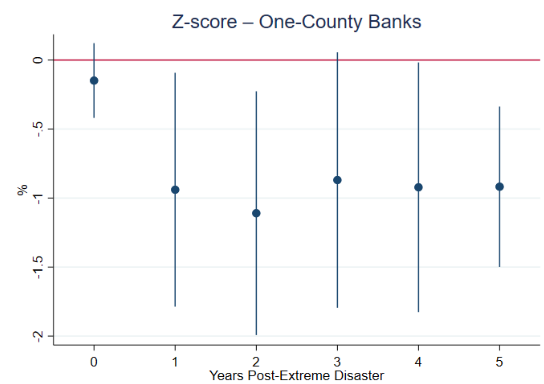
(c)



(d)



(e)



(f)

Figure 3: ***Note*** *This figure plots the scaled individual (non cumulative) coefficients and 95% confidence bands of our "extreme disaster" specification for the outcomes and bank type indicated. Coefficients are scaled to represent a one-standard deviation increase in disaster exposure on the outcome variable, relative to the unconditional full sample mean. They can be read as percent changes of the dependent variable. The figures make use of the most severe 10% of all disaster declarations, setting the value of all other events to 0 and controlling for their occurrence as binary variables.*

Table 1: *Disaster Frequency and Damages by Type, 1995–2018*

				Damages (millions USD)		
Type	Counties	County-quarters	Risk	Mean	Median	90th
Lightning	452	608	0.01	0.14	0.02	0.23
Heat	66	82	0.00	0.22	0.03	1.02
ThunderStorm	2146	5598	0.03	0.91	0.01	0.51
Wind	2450	7159	0.04	1.04	0.02	0.71
Hail	796	1436	0.01	1.43	0.02	0.60
Other	32	32	0.00	2.52	0.11	8.37
WinterWeather	1520	2723	0.02	4.41	0.32	10.04
Coastal	50	86	0.00	4.59	0.04	6.92
Drought	158	214	0.00	5.70	1.54	2.09
Tornado	1407	2594	0.02	6.93	0.27	11.16
Flooding	2652	8719	0.04	7.12	0.48	12.09
Landslide	112	155	0.00	12.59	0.23	24.86
Wildfire	313	496	0.01	20.15	1.87	50.34
Hurricane	794	1827	0.01	32.31	3.30	128.70

Note: This table shows the frequency of different type disasters type across across U.S. counties, county-quarter, and estimated property damages from Shieldus."Other" Disaster Type reports on Tsunami, Fog, and Avalanche disasters."Risk" is defined as the ratio of affected county-time observations to all county-time observations.

Table 2: *Disasters and Bank Summary Statistics, 1995—2018*

	Mean	St.Dev	25th	Median	75th	Obs
Panel A: One-County Banks						
Disaster exposure	0.84	1.61	0.00	0.00	1.21	36141
Total assets, $bn	0.12	0.14	0.04	0.08	0.14	36141
Charge-Off Rate, %	0.09	0.12	0.01	0.05	0.11	36141
Log(Net Inc.)	12.15	1.14	11.43	12.19	12.90	36141
RoA, %	0.28	0.14	0.19	0.27	0.36	36141
SD(Roa), %	0.00	0.00	0.00	0.00	0.00	32911
Cap. / Assets, %	10.59	3.04	8.49	9.90	11.91	36141
Z	134.53	91.57	68.65	112.37	177.40	32911
Log(Loans)	17.62	1.01	16.93	17.61	18.28	36141
Log(RRE)	16.06	1.47	15.29	16.25	17.04	36141
Log(SBL)	11.52	5.88	12.73	14.22	14.99	26561
Log(C&I)	15.53	1.28	14.69	15.54	16.38	36141
Log(Consumer)	14.93	1.18	14.26	14.99	15.68	36141
Int. Inc./Loans	2.64	1.01	1.92	2.50	3.12	36141
Panel B: Multi-County Banks						
Disaster exposure	1.17	1.75	0.00	0.00	2.29	50509
Total assets, $bn	1.17	4.26	0.11	0.23	0.53	50509
Charge-Off Rate, %	0.09	0.12	0.02	0.05	0.11	50509
Log(Net Inc.)	13.40	1.50	12.45	13.27	14.17	50509
RoA, %	0.27	0.13	0.19	0.26	0.34	50509
SD(Roa), %	0.00	0.00	0.00	0.00	0.00	48015
Cap. / Assets, %	9.42	2.08	8.02	9.03	10.35	50509
Z	145.28	96.01	75.63	123.06	191.69	48015
Log(Loans)	18.99	1.39	18.07	18.82	19.70	50509
Log(RRE)	17.48	1.55	16.54	17.40	18.31	50509
Log(SBL)	14.39	4.04	14.52	15.28	16.02	43471
Log(C&I)	17.00	1.58	15.96	16.86	17.83	50509
Log(Consumer)	15.96	1.51	15.03	15.81	16.66	50509
Int. Inc./Loans	2.16	0.70	1.62	2.03	2.60	50509

Note: Disaster exposure equals weighted exposure to disaster damages to county (see text for details). Chargeoffs are relative to total loans. RoA (return on assets) is quarterly. SD(RoA) equals five-year rolling standard deviation of quarterly RoA. Z equal (RoA + capital/assets)/SD(ROA). RRE = residential real estate loans. SBL = small business loans. Consumer loans includes credit card and installment loans. Statistics report quarter/year average. All outcomes, except "Disaster exposure", winsorized at (1,99).

Table 3: *Cumulative Disaster Impacts at Different Horizons*

	Charge-offs	log(Net inc.)	RoA	SD(RoA)	Cap/Assets	Z score
Panel A: One-County Banks						
1 year	-0.001	-0.011*	-0.002	0.000	0.000	0.238
3 year	0.001	-0.016	-0.003	0.000	0.012	0.106
5 year	0.001	-0.021	-0.005*	0.000	0.038	0.535
5 year $\times \sigma / \mu$	2.316	-0.280	-2.863*	0.000	0.576	0.641
Observations	21981	21981	21981	21030	21981	21030
Panel B: Multi-County Banks						
1 year	0.001	0.011*	-0.001	0.000	-0.018	1.650**
3 year	0.002	0.020**	0.000	0.000	-0.005	1.045
5 year	0.005**	0.022*	0.000	0.000	0.009	-0.330
5 year $\times \sigma / \mu$	9.751**	0.284*	0.000	0.000	0.170	-0.396
Observations	33932	33932	33932	33359	33932	33359
Panel C: All Banks						
1 year	0.001	0.006	-0.001	0.000	-0.012	0.523
3 year	0.003**	0.012	-0.000	0.000	0.004	0.013
5 year	0.005***	0.015	-0.001	0.000	0.030	-0.476
5 year $\times \sigma / \mu$	8.941***	0.194	-0.731	0.000	0.515	-0.575
Observations	62724	62724	62724	60588	62724	60588

Note: This table reports coefficient estimates from model (2) with the outcome indicated as the dependent variable. The model includes state $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes (for multi-county banks, a deposit-weighted mean of) county characteristics (per capita income, population, deposit HHI, unemployment rate, and percent white), bank characteristics (assets, assets^2, BHC and bank type indicators), and running counters of the number of previous disasters and number of previous FEMA disasters plus those in the next five years. The models are estimated using panel data over 1995q4—2018q4. The first row in each panel reports the sum of coefficients on $D_{b,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{b,t-1}$ divided by the mean of each outcome over the bank sample, times 100. Standard errors clustered by county for one-county banks; Newey-West standard errors (four lags) for multi-county bags. *, **, *** give significance at the 10, 5, and 1 percent levels.

Table 4: *Extreme (90th percentile) Disasters Impacts*

	Charge-offs	log(Net inc.)	RoA	SD(RoA)	Cap./Assets	Z Score
Panel A: One-County Banks						
1 year	0.004*	0.011	-0.004	0.000**	-0.127***	-4.508**
3 year	0.009*	0.067*	-0.003	0.000***	0.023	-13.304***
5 year	0.008	0.141*	-0.002	0.000**	0.239	-22.159***
5 year $\times\sigma/\mu$	4.632	0.625*	-0.358	0.000**	1.209	-8.825***
Observations	21981	21981	21981	21030	21981	21030
Panel B: Multi-County Banks						
1 year	0.007	0.055*	0.005	0.000	-0.068	0.587
3 year	0.001	0.105**	0.011**	0.000	-0.047	1.974
5 year	0.002	0.093*	0.009*	-0.000	0.016	5.870
5 year $\times\sigma/\mu$	0.000	0.119*	0.740*	0.000	0.032	0.714
Observations	33932	33932	33932	33359	33932	33359
Panel C: All Banks						
1 year	0.005*	-0.018	-0.004**	0.000***	-0.013	0.188
3 year	0.007*	-0.013	-0.006**	0.000***	-0.018	-0.019
5 year	0.007*	-0.018	-0.010***	0.000***	-0.012	0.144
5 year $\times\sigma/\mu$	3.353*	-0.054	-1.463***	0.000***	-0.040	0.038
Observations	62724	62724	62724	60588	62724	60588

Note: This table shows estimates of model (2) using FEMA disasters in the 90th percentile and unlogged damages. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes (for multi-county banks, a deposit-weighted mean of) county characteristics (per capita income, population, deposit HHI, unemployment rate, and percent white), bank characteristics (assets, assets^2, BHC and bank type indicators), and running counters of the number of previous disasters and number of previous FEMA disasters plus those in the next five years. The models are estimated using panel data over 1995q4—2018q4. The first row in each panel reports the sum of coefficients on $D_{b,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{b,t-1}$ divided by the mean of each outcome over the bank sample, times 100. Standard errors clustered by county for one-county banks; Newey-West standard errors (four lags) for multi-county bags. *, **, *** give significance at the 10, 5, and 1 percent levels.

Table 5: *The Impact of FEMA and non-FEMA Disasters on One-County Banks*

	Charge-offs	log(Net inc.)	RoA	SD(RoA)	Cap./assets	Z score
			Panel A: Exposure			
1 year	-0.006	-0.002	-0.001	0.000	0.013	0.206
3 year	-0.010	-0.006	-0.002	0.000**	0.025	-0.253
5 year	-0.013	-0.009	-0.001	0.000**	0.037	-0.599
5 year $\times\sigma/\mu$	-0.280	-0.908	-1.073	0.000**	0.926	-1.173
			Panel B: FEMA			
1 year	1.139***	0.053	0.211**	0.001	-1.178	-29.843
3 year	3.047***	-0.137	0.647***	-0.001	-0.327	73.609
5 year	3.812***	-0.828	0.768***	-0.001	-0.130	199.684
5 year $\times\sigma/\mu$	0.864***	-0.870	7.514***	0.000	-0.038	4.107
			Panel C: Exposure $\times$ FEMA			
1 year	-0.021**	-0.004	-0.004**	0.000	0.005	0.508
3 year	-0.046***	-0.006	-0.010***	0.000	-0.005	-0.584
5 year	-0.058***	0.007	-0.013***	0.000	0.009	-1.465
5 year $\times\sigma/\mu$	-0.765***	0.416	-7.514***	0.000	0.132	-1.751
Observations	21981	21981	21981	21030	21981	21030

Note: This table reports estimates of model (3) where we compare the impact of FEMA disasters and disaster events with damages from SHELDUS that are not declared as FEMA disasters. The impacts are estimated by regressing each bank outcome on an exposure measure positive for any (not only FEMA) disaster with nonzero damages, a FEMA dummy, and a FEMA damage exposure measure. FEMA represents a dummy that tracks whether the event in question receives a FEMA declaration. Finally, $D_{c,t-i} * FEMA_{c,t-i}$ is the interaction of the damage exposure faced by an individual bank with whether the disaster in question is a FEMA event. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes fixed effects indicated, county characteristics (per capita income, population, % white, deposit HHI, unemployment rate), and bank characteristics (assets, assets^2, BHC and bank type indicators). The models are estimated using panel data over 1995q4—2018q4. The first row in Panel A reports the sum of coefficients on $D_{c,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{c,t}$ divided by the mean of each outcome over the bank sample, times 100. Panel B reports the same for the coefficient on $FEMA_{c,t-i}$, and Panel C for the interaction. Outcomes winsorized at (1, 99). Standard errors clustered by county for one-county banks. *, **, *** indicate significance at the 10, 5, and 1 percent levels.

Table 6: *Identifying FEMA Effects Using Border Discontinuities*

	Charge-offs	log(Net inc.)	RoA	SD(RoA)	Cap./Assets	Solvency (Z)
Panel A: Exposure						
1 year	-0.001	0.004	0.001	0.000	-0.040**	0.712
3 year	-0.004*	0.013	0.001	0.000	-0.080**	1.193
5 year	-0.006**	0.021	-0.000	0.000	-0.099**	2.940
5 year $\times\sigma/\mu$	-22.004**	0.535	0.000	0.000	-2.919**	6.816
Panel B: FEMA						
1 year	0.039	-0.308	-0.045	-0.000	0.422	5.817
3 year	0.087	-0.658	-0.087	-0.000	1.159	-1.735
5 year	0.015	-1.148*	-0.076	-0.000	2.534	6.192
5 year $\times\sigma/\mu$	3.474	-2.000*	-5.725	0.000	5.063	0.974
Panel C: Exposure $\times$ FEMA						
1 year	-0.001	0.030	0.001	0.000	-0.027	-1.915
3 year	-0.001	0.059	0.002	0.000	-0.075	-2.232
5 year	0.008	0.092	0.000	0.000	-0.180	-4.444
5 year $\times\sigma/\mu$	20.846	1.745	0.000	0.000	-3.920	-7.622
Observations	7861	7289	7866	7526	7866	7526

Note: This table reports any mitigating effects of FEMA aid using discontinuities in FEMA declarations at state borders. Unique disaster identifiers are constructed for disaster observations of the same type affecting contiguous counties in the same month. The sample includes disasters that cross state lines, were subject to a FEMA declaration in at least one county, and affected at least one state in which none of the border counties declared a FEMA emergency. Bank-time observations are included in the sample if the bank operates solely in one county, and that county was affected 0 to 5 years ago by an included disaster. The impacts are estimated by regressing each bank outcome on an exposure measure positive for any (not only FEMA) disaster with nonzero damages, a FEMA dummy, and a FEMA damage exposure measure FEMA represents a dummy that tracks whether the event in question receives a FEMA declaration. Finally, $D_{c,t-i} * FEMA_{c,t-i}$ is the interaction of the damage exposure faced by an individual bank with whether the disaster in question is a FEMA event. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes fixed effects indicated, county characteristics (per capita income, population, % white, deposit HHI, unemployment rate), and bank characteristics (assets, assets^2, BHC and bank type indicators). The models are estimated using panel data over 1995q4—2018q4. The first row in Panel A reports the sum of coefficients on $D_{c,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{c,t}$ divided by the mean of each outcome over the bank sample, times 100. Panel B reports the same for the coefficient on $FEMA_{c,t-i}$, and Panel C for the interaction. Standard errors clustered by county for one-county banks; Newey-West standard errors (four lags) for multi-county bags. *, **, *** give significance at the 10, 5, and 1 percent levels.

Table 7: *Disaster Impacts on Loan Demand at Different Horizons*

	Total	Home Mort.	Small Business	C&I	Consumer	Int. / Loans
Panel A: One-County Banks						
1 year	-0.002	0.005	-0.006	-0.003	0.002	-0.005
3 year	-0.003	0.009	0.048	-0.004	-0.010	-0.013
5 year	-0.005	0.009	0.049	-0.004	-0.016	-0.011
5 year $\times\sigma/\mu$	-0.045	0.093	0.686	-0.039	-0.174	-0.681
Observations	21981	21981	19981	21981	21981	21981
Panel B: Multi-County Banks						
1 year	0.014***	0.016***	0.044	0.015***	0.009*	-0.003
3 year	0.024***	0.023***	0.059	0.025***	0.019**	-0.005
5 year	0.029***	0.025***	0.088	0.030***	0.029**	-0.005
5 year $\times\sigma/\mu$	0.269***	0.252***	1.070	0.306***	0.320**	-0.416
Observations	33932	33932	32797	33932	33932	33932
Panel C: All Banks						
1 year	0.011***	0.015***	0.047*	0.011***	0.008**	-0.003
3 year	0.019***	0.025***	0.067	0.020***	0.012*	-0.007**
5 year	0.025***	0.030***	0.100*	0.027***	0.018**	-0.005
5 year $\times\sigma/\mu$	0.228***	0.302***	1.279*	0.281***	0.200**	-0.338
Observations	62724	62724	59385	62724	62724	62724

Note: This table shows the impact of natural disasters with FEMA declarations and nonzero damages on the stock of bank loans by type. The impacts are estimated by regressing each bank outcome on a damage exposure measure and controls: $Y_{b,t} = \alpha + \sum_{i=0}^{5} \beta D_{b,t-i} + \delta C_{b,t} + \alpha_b + \omega_{s*t} + \chi_{s*d-type} + \epsilon_{b,t}$, where $D_{b,t-i} = log(\sum damages_{c,t-i} \times \frac{\sum branches_{b,c,t-i}}{\sum branches_{c,t-i}})/branches_{b,t-i}$ is a measure of bank b's exposure to disaster damage in period $t-i$. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes (for multi-county banks, a deposit-weighted mean of) county characteristics (per capita income, population, deposit HHI, unemployment rate, and percent white), bank characteristics (assets, assets^2, BHC and bank type indicators), and running counters of the number of previous disasters and number of previous FEMA disasters plus those in the next five years. The models are estimated using panel data over 1995q4—2018q4. The first row in each panel reports the sum of coefficients on $D_{b,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{b,t-1}$ divided by the mean of each outcome over the bank sample, times 100. Standard errors clustered by county for one-county banks; Newey-West standard errors (four lags) for multi-county bags. *, **, *** give significance at the 10, 5, and 1 percent levels.

Table 8: *Do Local Lenders Avoid High-Risk Floodzones?*

	Loan Accepted	**Log Loan Amount**	
	(1)	(2)	(3)
Local Bank	0.062***	-0.072***	-0.070***
	(0.000)	(0.010)	(0.010)
100-Year Floodzone	-0.013***	0.055***	0.021
	(0.000)	(0.005)	(0.020)
Local Bank × 100-Yr Floodzone	-0.01***	-0.085***	-0.109***
	(0.001)	(0.020)	(0.021)
Observations	89,757,403	89,757,403	89,757,403
Adjusted R^2	0.504	0.504	0.504
Outcome Mean	0.6	4.961	4.961

Notes: This table tests whether local banks (defined as banks with >50% of mortgage loans go to a single county) are less likely to lend (column (1))/ lend less (columns (2) and (3)) in 100-year floodzones than non-local banks. $Y_{i,b,l,t,c} = \alpha + \beta_1 FloodZone_c + \beta_2 LocalBank_{b,l} + \beta_3 FloodZone_c * LocalBank_l + \Omega_l + \gamma_i + \pi_t + \epsilon_{i,b,l,t,c}$ The equation of interest relates a loan-level outcome (representing either a binary variable taking on the value of 1 if loan i is accepted by both bank and borrower or the log size of an accepted loan) to whether a bank is local to a county. The regression includes controls for individual borrower *i* (including sex, race, income, dual applicant status), county/location fixed affects and time-varying characteristics *l* (ethnic makeup, mean income), bank characteristics *b* (whether a lender is local, lender type, lender size), a time fixed effect and – finally – the share of the census tract *c* that is designated a flood zone. The equation of interest relates a loan-level outcome (representing either a binary variable taking on the value of 1 if loan i is accepted by both bank and borrower or the log size of an accepted loan) to various characteristics of borrower b (including sex, race, income, dual applicant status), county characteristics (ethnic makeup, mean income), lender characteristics (whether a lender is local, lender type, lender size), a time fixed effect, and the local flood zone risk designation at the census tract –c– level. Only coefficients of interest are depicted for simplicity. Standard errors are clustered at the holding company level. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 9: *Do Local Lenders Avoid **Truly** High-Risk Floodzones?*

	DV: Log Loan Amount			
	Low Risk (< 3 Floods)		High Risk (> 5 Floods)	
	(1)	(2)	(3)	(4)
Local Bank	-0.077***	-0.075***	-0.017	-0.018
	(0.010)	(0.010)	(0.018)	(0.018)
100-Year Floodzone	0.048***	0.030	0.120***	0.016
	(0.005)	(0.020)	(0.009)	(0.032)
Local Bank × 100-Year Floodzone	-0.047**	-0.076***	-0.293***	-0.266***
	(0.020)	(0.021)	(0.052)	(0.048)
Observations	82,494,706	82,494,706	7,262,697	7,262,697
Adjusted R^2	0.507	0.507	0.465	0.465
Outcome Mean	4.969	4.969	4.860	4.860
Outcome SD	0.944	0.944	0.911	0.911

Notes: This table tests whether local banks (defined as banks with >50% of mortgage loans go to a single county) are likely to grant smaller loans in 100-year floodzones than non-local banks. $Y_{i,b,l,t,c} = \alpha + \beta_1 FloodZone_c + \beta_2 LocalBank_{b,l} + \beta_3 FloodZone_c * LocalBank_l + \Omega_l + \gamma_i + \pi_t + \epsilon_{i,b,l,t,c}$ The equation of interest relates a loan-level outcome (the log size of an accepted loan) to whether a bank is local to a county. The regression includes controls for individual borrower i (including sex, race, income, dual applicant status), county/location fixed affects and time-varying characteristics l (ethnic makeup, mean income), bank characteristics b (whether a lender is local, lender type, lender size), a time fixed effect and – finally – the share of the census tract c that is designated a flood zone. The equation of interest relates a loan-level outcome (representing either a binary variable taking on the value of 1 if loan i is accepted by both bank and borrower or the log size of an accepted loan) to various characteristics of borrower b (including sex, race, income, dual applicant status), county characteristics (ethnic makeup, mean income), lender characteristics (whether a lender is local, lender type, lender size), a time fixed effect, and the local flood zone risk designation at the census tract –c– level. Only coefficients of interest are depicted for simplicity. We split the sample according to whether the region has truly flooded in recent years or not. We distinguish between frequent >5 (columns (4) to (6)) and infrequent <3 floods (columns (1) to (3)). Standard errors are clustered at the holding company level. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

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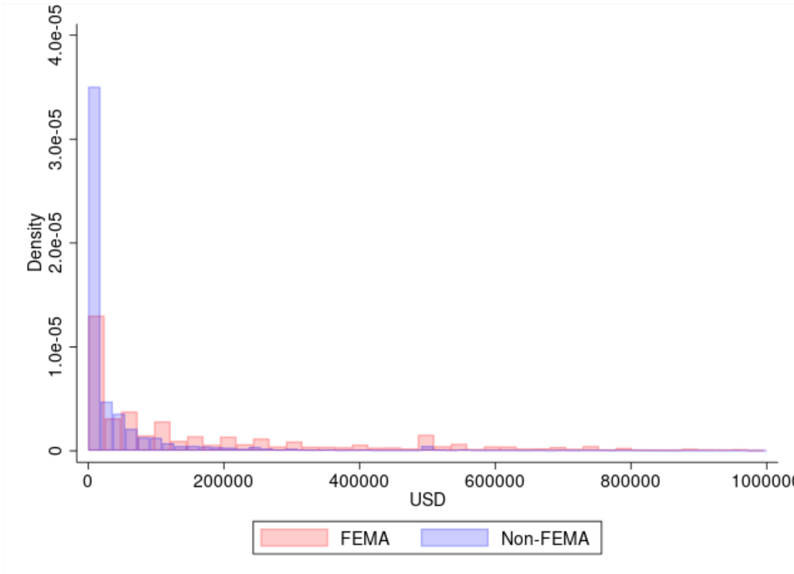
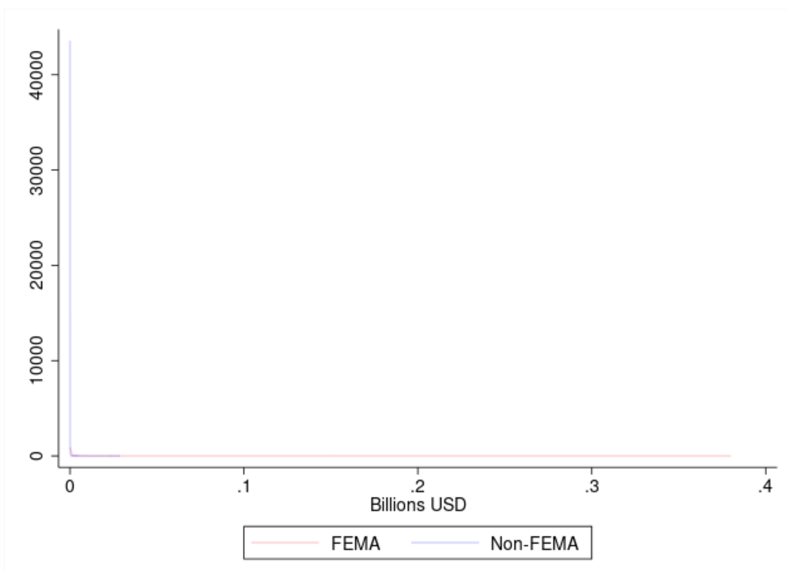
Appendix for "How Bad are Weather Disasters for Banks?"

Kristian S. Blickle, Sarah N. Hamerling, and Donald P. Morgan



(a) *Sheldus damages by disaster category*



(b) *Sheldus damages by disaster category – full sample*

Figure A.1: ***Disaster Damages:*** *This figure depicts damages wrought by major FEMA and non-FEMA disasters. Includes only disasters with damages greater than 0. We censor at 1 million USD for ease of viewing.*

(a) *Flood Zone Example Manhattan*

Figure A.2: ***FEMA Map*** *This map shows flood Hazards for lower Manhattan. Orange areas are 500-year (0.2%) flood risk zones and blue are the higher special hazard (100 year or 1%) flood zones.*

Table A.1: *Binary Exposure Measure*

	Charge-offs	Net inc.	RoA	SD(ROA)	Capital	Solvency (Z)
Panel A: One-County Banks						
1 year	-0.08	0.19	0.05	0.00	-0.65	-12.72
3 year	-0.17*	1.00*	0.23**	-0.00	0.21	27.01
5 year	-0.22*	1.19	0.23	-0.00	1.37	108.60
5 year $\times\sigma/\mu$	-11.58*	0.25	3.58	0.00	0.38	2.27
Observations	21981	21981	21981	21030	21981	21030
Panel B: Multi-County Banks						
1 year	-0.18**	1.20***	0.24***	-0.00***	-1.71	169.19***
3 year	-0.41***	1.97***	0.43***	-0.00***	-2.76	258.03***
5 year	-0.43***	2.40***	0.57***	-0.01***	-3.49	222.63*
5 year $\times\sigma/\mu$	-10.83***	0.37***	3.70***	0.00***	-0.74	3.05*
Observations	33928	33928	33928	33349	33928	33349
Panel C: All Banks						
1 year	-0.13***	0.69***	0.16***	-0.00*	-0.33	64.67*
3 year	-0.24***	1.32***	0.32***	-0.00**	0.09	124.74**
5 year	-0.27***	1.44***	0.35***	-0.00**	0.56	150.99*
5 year $\times\sigma/\mu$	-11.18***	0.23***	3.66***	0.00**	0.10	2.54*
Observations	62710	62710	62710	60571	62710	60571

Note: This table shows the impact of natural disasters with FEMA declarations and nonzero damages on bank performance and risk using an alternative binary exposure measure. The impacts are estimated by regressing each bank outcome on a damage exposure measure and controls: $Y_{b,t} = \alpha + \sum_{i=0}^{5} \beta D_{b,t-i} + \delta C_{b,t} + \alpha_b + \omega_{s*t} + \chi_{s*d-type} + \epsilon_{b,t}$, where $D_{b,t-i} = \sum \mathbb{1}_{c,t-i} \times \frac{\sum branches_{b,c,t-i}}{\sum branches_{c,t-i}} / branches_{b,t-i}$ is a measure of bank b's exposure to disasters in period $t-i$, where $\mathbb{1}_{c,t-1}$ equals 1 if a FEMA disaster of nonzero damages affected county c at time $t-1$. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes (for multi-county banks, a deposit-weighted mean of) county characteristics (per capita income, population, deposit HHI, unemployment rate, and percent white), bank characteristics (assets, assets^2, BHC and bank type indicators), and running counters of the number of previous disasters and number of previous FEMA disasters plus those in the next five years. The models are estimated using panel data over 1995q4—2018q4. The first row in each panel reports the sum of coefficients on $D_{b,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{b,t-1}$ divided by the mean of each outcome over the bank sample, times 100. Standard errors clustered by county for one-county banks; Newey-West standard errors (four lags) for multi-county bags. *, **, *** give significance at the 10, 5, and 1 percent levels.

Table A.2: *FEMA Treatment on One-County Banks, Disasters with > 25th FEMA Percentile and < 98th Non-FEMA Percentile Damages*

	Charge-offs	Net inc.	RoA	SD(ROA)	Capital	Solvency (Z)
Panel A: Exposure						
1 year	-0.01	-0.00	-0.00	0.00	0.01	0.32
3 year	-0.01*	-0.00	-0.00	0.00**	0.03	-0.30
5 year	-0.01	-0.01	-0.00	0.00**	0.05*	-0.79
5 year $\times \sigma / \mu$	-0.25	-1.13	0.00	0.00**	1.23*	-1.60
Panel B: FEMA						
1 year	1.06**	-0.14	0.16	0.00	-1.04	11.77
3 year	3.90***	-0.06	0.72***	-0.00	-0.11	179.90
5 year	5.22***	-0.65	0.93***	-0.00	-0.38	379.12*
5 year $\times \sigma / \mu$	0.99***	-0.38	7.16***	0.00	-0.09	6.43*
Panel C: Exposure $\times$ FEMA						
1 year	-0.02**	-0.00	-0.00	0.00	0.02	-0.21
3 year	-0.05***	-0.01	-0.01***	0.00	0.01	-2.05
5 year	-0.07***	0.01	-0.01***	0.00	0.03	-3.74
5 year $\times \sigma / \mu$	-0.91***	0.76	-7.16***	0.00	0.47	-4.29
Observations	21981	21981	21981	21030	21981	21030

The impacts are estimated by regressing each bank outcome on an exposure measure positive for any (not only FEMA) disaster with damages between the 25th and 98th percentiles of FEMA damages, a FEMA dummy, and a FEMA damage exposure measure: $Y_{b,c,t} = \alpha + \sum_{i=0}^{5} \beta_1 D_{b,t-i} + \sum_{i=0}^{5} \beta_2 FEMA_{c,t-i} + \sum_{i=0}^{5} \beta_3 D_{c,t-i} * FEMA_{c,t-i} \delta C_{b,c,t} + \epsilon_{b,c,t}$, where $D_{c,t}$ is the disaster exposure of bank b to a disaster affecting county c at t (year and quarter). FEMA represents a dummy that tracks whether the event in question receives a FEMA declaration. Finally, $D_{c,t-i} * FEMA_{c,t-i}$ is the interaction of the damage exposure faced by an individual bank with whether the disaster in question is a FEMA event. State $\times$ year, disaster type $\times$ state, county, bank, and quarter fixed effects are included. The control set C includes fixed effects indicated, county characteristics (per capita income, population, % white, deposit HHI, unemployment rate), and bank characteristics (assets, assets^2, BHC and bank type indicators). The models are estimated using panel data over 1995q4—2018q4. The first row in Panel A reports the sum of coefficients on $D_{c,t-i}$ for the first year, the second for the first three years, and the third for the first five years. The fourth row reports the five year sum times the st. dev. of $D_{c,t}$ divided by the mean of each outcome over the bank sample, times 100. Panel B reports the same for the coefficient on $FEMA_{c,t-i}$, and Panel C for the interaction. Outcomes winsorized at (1, 99). Standard errors clustered by county for one-county banks. *, **, *** give significance at the 10, 5, and 1 percent levels.