The impact of climate hazards on banks' long-run performance *

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September, 2023

Abstract

We investigate the impact of extreme climate hazards on banks' long-term loan losses and profitability, emphasizing the underlying transmission channels. Utilizing a comprehensive dataset of US hurricanes, we identify a distinctive pattern in bank performance. In the initial two years post-hurricane, banks exhibit decreased loan losses and improved profitability. However, this contrasts with elevated loan losses and diminished profitability in the longer run. We explore several explanations behind these patterns and determine that the improved short-term bank performance post-hurricane is partially attributable to disaster aid. Conversely, the aftermath of a hurricane sees a deterioration in loan quality, as banks increase lending to the now riskier, hurricane-impacted regions. This behavior precipitates a decline in their long-term performance. Additionally, the delays in recognizing loan losses further contribute to banks' risk-taking, amplifying long-term losses following hurricanes.

Keywords: Climate risk, hurricane, bank performance, disaster aid, risk-taking
JEL Classification: G21, M41, Q54

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*We thank Philip Berger, Jianfei Cao, Hans Christensen, John Gallemore, João Granja, Anya Kleymenova, Christian Leuz, Miao Liu, Shirley Lu, Maximilian Muhn, Thomas Rauter, Haresh Sapra, Douglas Skinner, Christopher Williams (discussant), and seminar participants at the University of Chicago, the 2022 CAPANA Conference, and the 2022 Yale SOM Summer Accounting Conference for helpful comments and suggestions. We benefited greatly from institutional insights that were provided by Robert Esquivel (SBA), Stuart Hinson (NOAA), and the OpenFEMA Team. All errors are our own.

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"[...]climate-related financial risks pose a clear and significant risk to the U.S. financial system and, if improperly assessed and managed, may pose a threat to safe and sound banking and financial stability." Martin J. Gruenberg, Acting Chairman, FDIC Board of Directors.

1 Introduction

With the rapidly mounting occurrence of adverse climate events, bank regulators around the world emphasize the potential risks climate change presents for the financial system and the need to incorporate these risks into the analysis of financial institutions (e.g., Board of Governors, 2020; FDIC's 87 FR 19507, 2022). Similarly, accounting regulators are pressing for the inclusion of climate-related hazards in credit risk assessments, provisioning for expected loan losses, and asset valuations, among others (IFRS Foundation, 2020; SEC's 87 FR 21334, 2022). While the critical importance of the financial sector's vulnerability to climate risks is widely recognized, there remains a substantial gap in our understanding of how climate-related risks manifest and, more critically, the mechanisms through which these risks influence the financial sector (Board of Governors, 2020). In particular, the open questions include understanding the long-term consequences of natural disasters on banks, whether banks internalize or transfer climate-related losses, and how lending practices and bank behavior shift in response to climate adversities. In this study, we seek to bridge this knowledge gap by focusing on the causal relationship between one of the most salient types of climate events – hurricanes – and the subsequent bank performance.

We focus on hurricanes for several reasons. First, among all types of climate hazards, hurricanes contribute the most to banks' physical climate risk because of the tremendous damage they cause in a very short period of time. Second, their landfalls are very difficult to predict, which gives us a sharp exogenous variation and statistical power necessary to identify the effect of climate hazards on banks' performance. Third, borrowers' losses from hurricanes are covered by flood insurance, which is the largest source of financial aid not available for most other types of natural disasters (e.g., wildfires) and which is largely exogenously determined. This enables us to shed light on the channels linking climate events and banks' performance.

We document an unexpected effect of major natural disasters on banks. Hurricane exposure causes a significant reduction in net charge-offs and an increase in return on assets in the first two years following the event. However, it simultaneously causes a reversed pattern in the subsequent years. The effects are economically significant. There is a 7% drop in loan losses in the first two years and a 6% increase in loan losses during years five to six following a hurricane. More extreme or unexpected hurricanes lead to even greater long-term losses with relatively smaller improvements in short-term performance. We show that these patterns cannot be explained by changes in banks' characteristics, business cycle fluctuations, or local economic trends. Furthermore, long-term loan losses following hurricane exposure are not reflected in banks' provisions and, hence, in banks' capital in a timely manner.

What can explain the puzzling patterns in bank performance we identify? We investigate three types of non-mutually exclusive economic explanations potentially contributing to these patterns. First, natural disasters, which have a long-lasting negative impact on the local economy (Boustan, Kahn, Rhode, and Yanguas, 2020; Jerch, Kahn, and Lin, 2020), are usually followed by financial aid to the affected areas. The aid funds, which come from multiple sources, aim to help the affected households and businesses to rebuild and to cope with the loss of income. However, financial aid injections can also give banks an opportunity to extract funds from borrowers in the form of interest and principal payments as well as originating fees. This can potentially explain increased banks' profits immediately following a hurricane, potentially indicating the passing of banks' losses onto borrowers.

Second, banks' lending practices are likely to change following a hurricane exposure. Increased demand for risky loans may create opportunities for banks to engage in increased risk-taking, which can be desirable if banks lend to the affected areas. To the extent financial aid helps insulate banks financially, it creates additional risk-taking incentives. Furthermore, bank regulators often give the affected banks increased flexibility in financial reporting to encourage recovery lending. Less stringent reporting requirements further reduce discipline and enable increased risk-taking. As a result of these factors, banks can generate additional profits in the short run due to higher interest and origination fees, but they are also likely to experience an increase in long-term losses associated with riskier loans.

Third, financial reporting practices can also play a role in how hurricanes influence banks' performance. Regulatory guidelines often encourage banks to offer loan forbearance or restructuring to borrowers in disaster-affected areas. This can involve a "grace period" during which loan payments and foreclosures are temporarily halted, effectively "freezing" the borrowers' past due status. Banks can also restructure the loans to defer the realization of loan losses. Such forbearance programs can have a positive effect on banks' short-term reported profits, but they are also expected to offset profits in the longer run. Besides forbearance, banks exhibit heterogeneity in the timeliness of loan loss provisioning. Less timely provisioning can exacerbate incentives for risk-shifting (Bushman and Williams, 2015), also increasing long-term losses.

We begin our analysis by examining the effect of financial aid on banks' performance. Financial aid following hurricanes comes from three primary sources: flood insurance claims, SBA loans, and FEMA grants, all of which can ultimately help the households meet the interest and principal obligations in the affected areas. Economically, flood insurance payment is the most significant source of aid. More importantly, its impact on banks is largely exogenous because its availability is determined based on historical flood maps.[1] Therefore, we focus on flood insurance payments to study the effect of financial aid.

We measure the affected bank's "flood insurance exposure" – an indicator of whether hurricane-affected counties that the bank lends to received flood insurance payments. We show that the presence of flood insurance significantly decreases the exposed bank's loan

[1] Flood insurance coverage is concentrated in the 100-year floodplains. Therefore, the influence of flood insurance payment on a hurricane-affected bank is randomly determined by the extent to which the hurricane affects 100-year floodplains. See Sections 2.2 and 2.3 for more details.

losses and increases ROA in the first two years following a hurricane. What is even more surprising is that banks' long-term losses increase in the presence of flood insurance, consistent with the notion that financial aid pads banks' performance and provides incentives to issue riskier loans. Overall, our results suggest that governmental disaster relief efforts indirectly strengthen bank profits following natural disasters.

We next turn to the increased risk-taking explanation. To probe it, we examine whether exposure to hurricanes leads to changes in lending standards towards riskier loans. We show that loans in the year(s) immediately following hurricane exposure are systematically different compared to the pre-hurricane loans. This change is responsible for significantly higher loan losses and lower ROA two to five years following a hurricane. Similar to the baseline results, banks do not capture increased losses in their provisions in a timely manner. Loan loss provisions and allowances do not significantly increase until two years after banks' post-hurricane lending, i.e., the time when loan losses start to increase. These results support the explanation that increased risk-taking contributes to banks' long-term underperformance.

We also provide more granular evidence of increased risk-taking by zooming in on banks' lending practices. Using bank-year-level and bank-county-year-level mortgage and small business loan lending data, we show that hurricane exposure leads to a significant shift to "recovery lending", i.e., lending to the affected counties following a hurricane strike, whereas banks exhibit an insignificant change in total loans. We also observe that mortgage interest rates increase with hurricane exposure. Collectively, these findings line up with the view that the affected banks shift lending to riskier (hurricane-affected) regions, thus performing a socially valuable function.

Finally, we explore whether reporting practices contribute to the effect of hurricanes on banks' risk-taking and long-term performance. We use loan delinquency as a proxy for loan forbearance. Forbearance typically follows delinquency after extreme events such as hurricanes and has been measured by delinquency in prior research (Kim, Lee, Scharlemann, and Vickery, 2022; Del Valle, Scharlemann, and Shore, 2022). We do not find evidence that delinquent loans change significantly after hurricanes. We also find that nonaccrual loans, which capture borrowers' financial difficulties, significantly decline in the first two years after hurricanes, indicating that borrowers' repayment ability indeed improved after hurricanes. Overall, these results suggest that the decline in banks' reported loan losses in the first two years after hurricane exposures is unlikely due to an increase in forbearance. To measure the delayed loss recognition, we rely on the expected loss overhang (OVH) developed by Lu and Nikolaev (2022). OVH is a quarterly proxy for expected loan losses that have not been provisioned for and suits well for the purpose of measuring delays in long-term loss recognition. We find that banks with greater delays increase risk-taking in the year of a hurricane and the following year, which contributes to banks' long-term underperformance.

Our study contributes to a growing literature on climate risks confronting financial institutions. We document an unexpected non-linear impact of climate hazards on the long-term performance of banks. Our paper is related to Blickle, Hamerling, and Morgan (2021) who find mixed or insignificant effects of climate hazards on bank performance, especially in the short run (see Figure 3 for more details). Our paper diverges in several pivotal ways.[2] First, we zero in on hurricanes, which offers a more powerful setting to examine banks' vulnerability to climate risks. This reveals the non-linear pattern in banks' performance. Second, we contribute by delving into the mechanisms by which natural disasters influence banks' outcomes. Our findings suggest that while disaster relief boosts banks' short-run profitability, banks' own actions lead to their long-run underperformance. Exploring the mechanisms helps us uncover adverse long-term consequences of climate events on banks, which are less evident and under-documented in the literature. In this sense, our paper is related to Billings, Ryan, and Yan (2022), who find that banks have increased their exposures to long-term climate risks through channels involving population migration and banks' local market knowledge.

[2]Blickle, Hamerling, and Morgan (2021) find mixed effects of climate hazards, e.g., disasters do not affect loan losses of banks operating in one county but significantly increase long-term loan losses of multi-county banks. In contrast to our study, they examine the average effect of *all* climate disasters. Further, they measure disaster aid using an indicator of whether a disaster receives FEMA support. In contrast, we use banks' exposure to flood insurance payments. We find that FEMA support, which is relatively small, cannot explain the significant effect of the financial aid.

Our findings also add to the accounting literature on the timeliness of loan loss provisioning in the context of climate risks. Prior evidence suggests that delayed provisioning increases banks' lending capacity and incentivizes risk-shifting (Beatty and Liao, 2011; Bushman and Williams, 2012, 2015). However, the interactions between provisioning for losses and climate-related events are not well understood. Our paper complements these studies by documenting delayed loan loss provisioning following climate hazards and its role in banks' long-term performance. Our findings also suggest that delayed provisioning can be socially desirable in the post-hurricane period to the extent it facilitates recovery lending. In a related study, Chamberlain, Vijayaraghavan, and Zheng (2019) examine banks' timeliness of loan losses after hurricanes. However, they do not investigate how delaying expected loss recognition contributes to banks' risk-taking and long-term performance after hurricanes.

Our paper should be of interest to financial regulators for at least three reasons. First, our findings suggest that the primary driver of a bank's post-hurricane performance is its *response to* a hurricane. Hence, focusing regulatory efforts on monitoring bank actions *after* climate events can be helpful in managing the effect of physical climate risks on the banking system. This is especially true for highly unpredictable climate hazards like hurricanes, for which taking precautionary actions in advance could be costly and ineffective. Second, we find that governmental disaster aid has a spillover effect in stabilizing the banking system in the short term after climate hazards. This positive externality provides a new potential justification for governmental disaster relief actions. Finally, we reveal a trade-off in banks' response to climate hazards. On the one hand, by shifting lending to disaster-affected regions, banks provide critical support to disaster victims. On the other hand, however, increased risk-taking amplifies banks' exposure to physical climate risks and weakens banks' long-term performance.

2 Background

2.1 US banks' climate risk from hurricanes

Among different types of climate-related hazards, hurricanes contribute the most to US banks' exposure to climate risks. Hurricanes' devastating effects lead to large financial shocks to bank borrowers, and their unpredictable nature exacerbates banks' vulnerability to these shocks. The Federal Reserve's financial stability monitoring framework highlights the introduction of financial shocks and increased vulnerability as principal channels through which climate risks can impact the financial system (Board of Governors, 2020).

According to the National Oceanic and Atmospheric Administration (NOAA), hurricanes contributed over 53% of the $1.9 trillion total loss caused by major natural disasters (each costing more than $1 billion) in the US from 1980 to 2020 and caused the highest per event losses with the greatest number of death per year (Smith, 2021). Hurricanes not only cause significant damage but are also highly unpredictable. Weather patterns that determine hurricane landfalls are only predictable when the hurricane is within several days of making landfall. As a result, NOAA does not provide seasonal hurricane landfall predictions.[3]

Due to the pronounced climate risk that hurricanes present to the banking system, our study concentrates on these events when examining the effects of climate hazards on banks. We have chosen this focus not only because of the profound and unpredictable financial shocks hurricanes induce but also because they provide a distinct exogenous variation, ensuring robust statistical analysis. Furthermore, hurricane-related losses are compensated by flood insurance payments, a vital source of disaster assistance. This feature aids in understanding the channels through which hurricanes influence banks. We delve deeper into this aspect in Section 3.2.1.

[3] See, for example, NOAA 2021 Atlantic Hurricane Season Outlook: https://www.cpc.ncep.noaa.gov/products/outlooks/hurricane.shtml

2.2 Governmental disaster aid and bank loan forbearance

The federal government provides multiple forms of support to victims of hurricanes (and other natural disasters) to mitigate their economic losses. The primary sources of financial support from federal agencies are flood insurance claims from the National Flood Insurance Program (NFIP), low-interest-rate disaster loans provided by the Small Business Administration (SBA), and direct cash grants from the Federal Emergency Management Agency (FEMA) (Drexler, Granato, and Rosen, 2019). The NFIP flood insurance is economically the largest source of hurricane-related disaster aid. It provides residential coverage up to \$250,000 for buildings and up to \$100,000 for contents. The insurance is required for federally guaranteed mortgages in 100-year floodplains, while residents living outside these areas rarely purchase the insurance (Billings, Gallagher, and Ricketts, 2022). SBA provides up to \$200,000 disaster loans for households to replace or repair their primary residence, with interest rates as low as 1.25% and terms up to 30 years. FEMA provides financial assistance through grants that do not need to be repaid, with a cap of \$37,900 for housing assistance and \$37,900 for other needs assistance as of 2021 (86 FR 63046).

In addition to the federal government, banks themselves offer loan forbearance for borrowers affected by hurricanes. Banks can grant a "grace period," typically ranging from 30 days to 12 months, during which banks reduce or suspend mortgage payments, suspend foreclosures, and waive penalties for borrowers with hurricane-damaged homes (e.g., Freddie Mac, 2017; Fannie Mae, 2017). Banks can also restructure loan repayment terms and schedules for affected borrowers who can no longer afford to resume payments.

Bank forbearance provides important short-term financial relief to hurricane victims. For example, while banks experienced increased loan delinquencies after Hurricane Harvey, they did not report hurricane-related delinquencies to credit bureaus (Hartley, Packis, and Weintraut, 2019). As a result, borrowers who missed payments after the hurricane did not experience a decline in credit scores (Del Valle, Scharlemann, and Shore, 2022).

To encourage banks to "work constructively" with affected borrowers, bank regulators usually expand banks' flexibility in financial reporting after disasters. As long as banks make reasonable efforts to comply with the regulatory requirements in reporting items such as loan loss provisions and charge-offs, regulators will not punish banks if their financials do not fully meet the reporting requirements following a hurricane (e.g., FFIEC, 2005; Federal Reserve, 2017). Banks are expected to gradually improve the accuracy of their reporting only "as information becomes available."

2.3 Hypothesis development

A number of factors contribute to bank performance in the short and long run after experiencing a hurricane shock. In this section, we identify three potential channels that can explain the non-linear effect of hurricanes on banks' long-term performance.

2.3.1 Disaster aid channel

First, we argue governmental disaster assistance to the affected households and businesses can be indirectly responsible for the strengthening of bank profits in the short term. For example, NFIP made an estimated \$8.92 billion insurance payouts to about 92,000 Texans after Hurricane Harvey (FEMA, 2019), which suggests a \$97,000 average payout per affected resident. To put the average number into context, the average amount of property damage incurred due to 1 foot (3 feet) of flooding in a home is \$72,162 (\$94,538), according to National Flood Services cost tables. In addition, SBA approved over \$2.9 billion individual home loans for Harvey victims, with an average approved loan amount of \$79,183, and FEMA provided \$1.6 billion grants, with an average of \$7,446 (Billings, Gallagher, and Ricketts, 2022).

The significant cash inflows from disaster assistance can help affected borrowers recover their financial losses and continue their debt repayment. The aid can even allow debt repayment for borrowers who would have otherwise defaulted in the absence of hurricane exposure.[4] In addition, hurricane victims can, and many choose to, use the financial aid they received to pay down debt rather than repair houses, especially when the rebuilding cost exceeds the home value. Banks also have the incentive and ability to press borrowers to use these funds to repay mortgages first because some of the funds, such as flood insurance payments, are held in escrow by the lender for homes used as collateral of mortgages (Gallagher and Hartley, 2017). Therefore, we make the following prediction:

Hypothesis 1: The availability of disaster aid contributes to banks' improved short-term financial performance after experiencing hurricanes.

2.3.2 Risk-taking channel

Changes in banks' risk-taking behavior following hurricanes represent another potential channel behind banks' long-term performance. Despite the presence of financial aid, households and businesses affected by natural disasters often need to borrow significant amounts from banks to raise funds to rebuild damaged homes and businesses. This leads to a sharp increase in demand for credit in the affected regions (Cortés, 2014; Cortés and Strahan, 2017). Much of this demand is likely to constitute considerable risks for banks as hurricanes have a long-lasting adverse effect on the local economy. The increased demand can push up loan prices (interest rates) in hurricane-affected areas and make lending attractive, especially in the short run. As a result, banks potentially face incentives and opportunities to relax credit standards and increase risk-taking. These incentives are potentially amplified by the presence of governmental disaster aid that helps borrowers to make payments in the short run and hence helps to insulate banks financially. In addition, regulators directly encourage banks to increase lending to hurricane-affected regions to help economic recovery (e.g., Federal Reserve, 2017).

[4] Consistent with these arguments, prior research finds that household debt, defaults, and foreclosures decline after hurricanes and other natural disasters and that the decline is more pronounced after more severe disasters (Issler, Stanton, Vergara-Alert, and Wallace, 2020; Billings, Gallagher, and Ricketts, 2019; Gallagher and Hartley, 2017; Overby, 2007). These papers attribute the decline to disaster assistance and increased debt repayment.

While increased risk-taking can increase banks' profitability in the short term, e.g., due to increased interest payments and fees, it can undermine banks' performance in the long term when loan losses are likely to pick up. Lending in hurricane-affected areas can increase banks' long-term losses because of the long-term damage hurricanes inflict on the local economy. Indeed, prior research finds that hurricanes lead to decade-long declines in firm productivity, wages, family income, housing prices, population, and local governments' revenues, expenditures, and investment (Boustan, Kahn, Rhode, and Yanguas, 2020; Jerch, Kahn, and Lin, 2020). By increasing banks' exposure to hurricane-related long-term risks, recovery lending can contribute to banks' long-term losses after hurricanes. Accordingly, we make the following prediction:

Hypothesis 2: Banks increase lending to hurricane-affected regions in the short term after experiencing hurricanes, which contributes to banks' deteriorated performance in the long term.

2.3.3 Financial reporting channel

Financial reporting practices can explain the effect of hurricanes on banks' performance via two channels. First, loan forbearance can be responsible for improved reported performance of a bank in the short term. Regulators encourage banks to practice forbearance in response to hurricanes to mitigate the financial difficulties faced by hurricane victims (e.g. Federal Reserve, 2017) while simultaneously relaxing reporting requirements. Suspending borrowers' loan repayments and foreclosures "freezes" their past-due status, reducing banks' reported charge-offs (FFIEC, 2005; Del Valle, Scharlemann, and Shore, 2022). Loan restructuring also generates fees and reduces lenders' loan losses in the short term, as it helps borrowers avoid default by lowering interest rates or extending repayment terms. While loan forbearance allows borrowers to delay payments, it does not reduce their debt levels. Therefore, borrowers can still default in the long term if their repayment abilities do not meaningfully recover after hurricanes. Overall, loan forbearance can explain banks' improved performance in the short term and its reversal in the long term after hurricanes. Based on these arguments, we make the following prediction:

Hypothesis 3A: Banks' increased loan forbearance is responsible for superior short-term performance after hurricane exposure.

Another reporting channel that can help explain bank performance after hurricanes is untimely loan loss provisioning. Delaying loan loss recognition builds an overhang of unrecognized losses, which inflates the reported capital and degrades bank transparency; it thus encourages risk-taking behavior (Bushman and Williams, 2012, 2015; Akins, Dou, and Ng, 2017; Lu and Nikolaev, 2022). Banks can delay loan loss recognition after hurricanes if their strong short-term performance leads to underestimated credit risks (Bordalo, Gennaioli, and Shleifer, 2018). In addition, because regulators give banks more flexibility in financial reporting after hurricanes due to the heightened uncertainty (e.g. FFIEC, 2005), banks have more opportunities and incentives to delay loan loss recognition. We make the following prediction:

Hypothesis 3B: Banks' delays in loan loss recognition contribute to banks' improved performance in the short term and deteriorated performance in the long term.

3 Research design

In this section, we discuss our research design and how the design addresses key identification issues in analyzing hurricanes' impact on bank performance and the potential mechanisms involved.

3.1 Identifying the impact of hurricanes on bank performance

In our baseline analysis, we focus on identifying the long-term effect of hurricane exposure on bank performance. To do so, we leverage the exogenous and, as discussed previously, hard-to-predict nature of their landfall. We also take additional care to ensure that the effect is not driven by changes in other bank characteristics or local economic trends in the regions more susceptible to natural disasters.

Specifically, we study how the levels of banks' realized loan losses, profitability, and loan loss provisioning change in response to bank's hurricane exposure up to seven years into the future. Formally, we use bank-quarter-level data to run the following regressions:

$$Performance_{i,t} = \beta_0 + \sum_{h=t-7}^{h=t-1} \beta_h HurrExposure_{i,h} + \gamma X_{i,t} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \tag{1}$$

$Performance$ represents NCO, ROA, LLP, or ALL, defined as follows. NCO is net charge-offs scaled by the average loan balance. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $HurrExposure_{i,t}$ is a bank's hurricane exposure, which we define and discuss below. All income statement items are measured quarterly but are annualized by summing their values in the current and preceding three quarters. $t-1$ through $t-7$ refer to one- to seven-year lags before the current year-quarter t. We estimate the above model each quarter but using annualized variables. This approach mitigates the effect of seasonality and allows us to examine the impact of hurricane exposure in each of the next seven years while giving us more power than using annual-level data.[5]

Since performance outcomes are related to bank characteristics, we control the following factors (included in X): size, capital ratio, loan type, loan maturity, and loan yield. We include bank fixed effects, α_i, to control for time-invariant bank characteristics that can contribute to their response to hurricanes. Finally, because hurricanes' impact can differ across geographical areas, and the impact can change over time, we include state $\times$ year-quarter fixed effects, $\alpha_{s,t}$, which help us isolate state-level time trends.

The key independent variable of interest, $HurrExposure_{i,t}$, is bank i's exposure to a

[5]For these reasons, prior research has used annualized variables measured quarterly in regressions (e.g., Harris, Khan, and Nissim, 2018; Lu and Nikolaev, 2022).

hurricane in quarter t. To calculate this measure, we first sum property losses from hurricanes across all counties while weighting them by bank i's mortgage market share in each county in quarter t. We then scale the weighted sum by the bank's lagged total loans and make a log transformation of this ratio to mitigate the effect of extreme weather events.[6] Formally:

$$HurrExposure_{i,t} = log\left(\frac{\sum_c HurrLoss_{c,t} * MortgageShare_{i,c,t}}{Loan_{i,t-1}} * 10^{14} + 1\right)/10^5 \qquad (2)$$

$HurrLoss_{c,t}$ is the dollar amount of property losses caused by hurricanes in county c in quarter t; $MortgageShare = \frac{OwnedMortgage3yr_{i,c,t}}{OwnedMortgage3yr_{c,t}}$, where $OwnedMortgage3yr_{i,c,t}$ is the dollar amount of mortgages issued and held by bank i in county c in the three years ending in the year of quarter t, and $OwnedMortgage3yr_{c,t}$ is the dollar amount of mortgages issued and held by all banks in the same county and the same period. $Loan_{i,t-1}$ is bank i's loans outstanding at the end of the previous year.

$HurrExposure_{i,t}$ is calculated following Cortés and Strahan (2017) with two modifications to fit our setting. First, we measure a bank's exposure to a county based on its share of mortgage amount instead of its share of branches (as in their paper) because mortgage market share is more likely to capture a bank's actual exposure to a county's total property lending (and thus the county's property losses from hurricanes). Second, we take the log transformation on the ratio of the weighted sum of hurricane losses to total lending instead of taking the log transformation only on the weighted sum before scaling it by total lending (as they did). This makes it easier to interpret $HurrExposure_{i,t}$ as a log transformation of the ratio of a bank's exposure to hurricane-related property losses to its total lending. Because of these changes, we need to multiply $\frac{\sum_c HurrLoss_{c,t} * MortgageShare_{i,c,t}}{Loan_{i,t-1}}$ by a sufficiently large number, i.e., 10^{14}, and scale the log transformation by 10^5 such that $HurrExposure$ does not have a long-tail distribution and that the regression coefficients are easy to interpret.

[6] See Section 4 and Figure 3 for more details on the effect of the log transformation.

3.2 Identifying channels underlying hurricanes' impact on banks

3.2.1 Disaster aid channel

To test the first hypothesis – the influence of governmental assistance on the relationship between hurricanes and bank performance – we require variation in financial aid that is independent of the event size or other factors that contribute to banks' performance.

A key challenge with uncovering such variation is that disaster aid is inherently endogenous. For example, SBA disaster loans and FEMA grants are more likely to cover wealthier borrowers with higher credit quality. The SBA explicitly limits disaster loans to applicants with acceptable credit history and repayment ability. Billings, Gallagher, and Ricketts (2022) find that regions with higher-ability-to-repay residents are more likely to receive SBA loans. These authors also find that FEMA is more likely to provide disaster relief grants to wealthier regions, as the complex approval process makes grants less accessible to low-income households. Therefore, any effect of these two sources of aid on banks' post-hurricane performance (e.g., reducing loan losses) can be explained by better economic conditions in regions receiving the aid.

To address this issue, we leverage a specific type of disaster aid – flood insurance. Flood insurance is the largest source of hurricane assistance, and at the same time, it is less susceptible to endogeneity issues because flood insurance coverage is primarily determined by FEMA's flood maps. The coverage is concentrated in the 100-year floodplains, where the insurance is required for federally guaranteed mortgages, while households outside these areas rarely have coverage (Drexler, Granato, and Rosen, 2019; Billings, Gallagher, and Ricketts, 2022). Flood insurance coverage among single-family homes is about 50% (1%) within (outside) the 100-year floodplains (Drexler, Granato, and Rosen, 2019). In addition, the impact of hurricanes on floodplains is random and varies considerably between hurricanes. For example, only 23% (over 90%) of the most flooded quartile of blocks were in a designated floodplain after Hurricane Harvey (Hurricane Katrina) (Gallagher and Hartley, 2017;

Billings, Gallagher, and Ricketts, 2022). Therefore, the variation in a bank's exposure to flood insurance payments is randomly determined by the extent to which a hurricane affects floodplains. Importantly, because flood insurance payments are not driven by victims' income level or credit quality, they can help low-credit-quality borrowers repay debt and explain the reduced bank losses in the short term after hurricanes.

We run the following regressions to study the influence of disaster aid on banks' post-hurricane performance:

$$\begin{aligned} Performance_{i,t} =& \beta_0 + \sum_{h=t-7}^{h=t-1} \beta_h HurrExposure_{i,h} * FloodInsurance_{i,h} \\ &+ \sum_{h=t-7}^{h=t-1} \eta_h HurrExposure_{i,h} + \sum_{h=t-7}^{h=t-1} \theta_h FloodInsurance_{i,h} \\ &+ \gamma X_{i,t} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

$FloodInsurance_{i,h}$ is an indicator variable that equals one if at least one of the hurricane-affected counties that Bank i is exposed to received hurricane-related flood insurance payment in quarter h, and zero otherwise. Other variables are defined as previously. X controls for bank characteristics that are associated with performance outcomes. Bank fixed effects, α_i, and state $\times$ year-quarter fixed effects, $\alpha_{s,t}$, control for time-invariant bank characteristics and state-level time trends that affect bank performance.

3.2.2 Risk-taking channel

To test our second hypothesis – risk-taking channel – we utilize the idea that a shift in risk-taking should cause a discontinuity in lending behavior around the hurricane occurrence. To identify such discontinuity, we examine whether bank lending immediately after a hurricane exposure is systematically different compared to lending before the exposure. More specifically, we examine whether loan growth immediately before the hurricane translates into lower long-term losses (higher long-term performance) as compared to loan growth after the hurricane. In other words, we use loan growth to capture banks' risk-taking activities (e.g., Baron and Xiong, 2017; Fahlenbrach, Prilmeier, and Stulz, 2018) and test whether these activities become riskier following hurricane exposures. To do so, we run the following regressions:

$$
\begin{aligned}
Performance_{i,t} =& \beta_0 + \sum_{h=t-7}^{h=t-1} \beta_h Past1YrHurrExp_{i,h} * \Delta Loan_{i,h} \\
&+ \sum_{h=t-7}^{h=t-1} \eta_h Past1YrHurrExp_{i,h} + \sum_{h=t-7}^{h=t-1} \theta_h \Delta Loan_{i,h} + \gamma X_{i,t} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t}
\end{aligned} \tag{4}
$$

$Past1YrHurrExp$ is the sum of $HurrExposure$ over the four quarters before the current quarter, h. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. We also control for bank characteristics that are associated with performance outcomes. Finally, we include bank fixed effects, α_i, and state $\times$ year-quarter fixed effects, $\alpha_{s,t}$, to control for time-invariant bank characteristics and state-level time trends that affect bank performance.

To provide further evidence on banks' risk-taking, we zoom in on banks' lending behavior at the regional level following a hurricane. We investigate whether banks increase risk-taking by lending to regions affected by hurricanes, which we define as recovery lending. In this analysis, we exploit bank-county-year-level mortgage and small business lending data to quantify banks' recovery lending. Recovery lending comes with substantial risks because hurricanes have a long-term negative effect on the local economy (Boustan, Kahn, Rhode, and Yanguas, 2020; Jerch, Kahn, and Lin, 2020). We also examine the effect of hurricanes on the loan prices banks charge, as increased interest rates can be viewed as an indirect measure of risk-taking.

To test whether hurricane exposure increases a bank's lending and loan prices in the counties affected, we use the following regression:

$$
RecoveryLending_{i,t} = \beta_0 + \beta_1 * HurrExposure_{i,h} + \gamma X_{i,h} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \tag{5}
$$

RecoveryLending represents one of the following variables: $\Delta MortRec$, $\Delta SBLRec$, $ShareRec$, or $SpreadRec$. $\Delta MortRec$ ($\Delta SBLRec$) is mortgage (small business) recovery lending, which is non-agency mortgages (small business loans) issued to counties that experienced hurricanes in year h minus mortgages (small business loans) issued to the same counties in year $h-1$, scaled by lagged total loans outstanding. $ShareRec$ ($SpreadRec$) is a measure of loan price, which is the $Share$ ($Spread$) of recovery mortgage lending. $Share$ is the proportion of mortgages issued with a positive spread over 3% plus the yield on Treasury securities of comparable maturity. $Spread$ is the average spread of mortgages with a positive spread. Subscript h refers to t or $t-1$ period. X controls for bank characteristics that affect lending. Bank fixed effects, α_i, and state × year-quarter fixed effects, $\alpha_{s,t}$, control for time-invariant bank characteristics and state-level time trends that affect banks' lending behavior.

3.2.3 Financial reporting channel

To test our third hypothesis, we separately explore whether (i) loan forbearance and (ii) delayed loan loss recognition contribute to banks' post-hurricane performance.

Forbearance. It is challenging to measure banks' forbearance activities as they are inherently opaque. In line with prior research, we use loan delinquency (i.e., past-due) status as a proxy for loan forbearance. Indeed, loan deferrals are either automatically provided to borrowers who miss payments following a hurricane or are often granted to borrowers who apply for forbearance because of difficulties in making repayments. In either case, forbearance follows delinquency. In addition, forbearance freezes the past-due status of the delinquent loans in banks' financial reporting.[7] As a result, forbearance can be captured by increases in delinquency after hurricanes. Consistent with this conjecture, prior research documents that forbearance goes up with delinquency after extreme events such as Hurricane Harvey and COVID-19 and that the increased delinquency during these periods does

[7]See regulators' guidance for financial institutions in response to Hurricane Katrina and COVID-19: https://www.ffiec.gov/katrina.htm, https://www.ffiec.gov/katrina.htm.

not affect borrowers' credit scores (Kim, Lee, Scharlemann, and Vickery, 2022; Del Valle, Scharlemann, and Shore, 2022; Hartley, Packis, and Weintraut, 2019). We also supplement the delinquency test by examining the change in nonaccrual loans. Usually, regulators do not change the reporting requirements for nonaccrual loans under deferral programs.[8] Therefore, if the decline in charge-offs after a hurricane is primarily due to loan forbearance, we should not see a decline (or see a much weaker decline) in nonaccrual loans.

We estimate the following regressions to examine the change in forbearance after hurricanes:

$$Forbearance_{i,t} = \beta_0 + \sum_{h=t-7}^{h=t-1} \beta_h HurrExposure_{i,h} + \gamma X_{i,t} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \tag{6}$$

Forbearance represents loans that are past due 90 days or more (or 30 through 89 days) and still accruing, scaled by total loans outstanding, or nonaccrual loans scaled by total loans outstanding. X controls for bank characteristics that affect forbearance measures. Bank fixed effects and state × year-quarter fixed effects control for time-invariant bank characteristics and state-level time trends that affect banks' past due and nonaccrual loans.

Delayed recognition. To evaluate the role of delayed loan loss recognition, we first compare the post-hurricane loan loss provisions or allowances with that of loan losses using Model 1. If, like loan losses, the allowances and provisions for losses also decline in the short run while reversing in the long run, then short-term provisioning is presumably insufficient in capturing the long-term increases in loan losses.[9] This comparison evaluates the overall

[8] For example, after Hurricane Katrina, regulators still required banks to "refer to the applicable regulatory reporting instructions, as well as its internal accounting policies, in determining whether to report loans to affected customers on which payments have been temporarily deferred as nonaccrual assets in regulatory reports." On the contrary, banks are allowed to apply charge-off policies in a more flexible way. They need to record charge-offs only when "information becomes available indicating a specific loan will not be repaid" (FFIEC, 2005).

[9] The idea of evaluating the timeliness of realized loss recognition by comparing current provisioning with future losses is similar to the idea underlying provisioning timeliness measures in prior research such as Akins, Dou, and Ng (2017), Balakrishnan and Ertan (2021), and Yang (2021). One important difference is that these papers focus on banks' provision for short-term losses while we look at the provision's ability to capture long-term losses.

provision timeliness from an ex-post point of view.

Second, we explore the effect of the delayed recognition of long-term loan losses after hurricanes. We expect that delayed provisioning exacerbates risk-taking incentives (Bushman and Williams, 2015) and hence contributes to the documented pattern of long-term underperformance. To measure the delay in recognizing long-term loan losses at the bank-quarter level, we rely on the expected loss overhang, OVH, introduced by Lu and Nikolaev (2022). OVH is calculated by subtracting reported allowance from the estimated long-term expected loan losses ($ExpLoss$). $ExpLoss$ is an out-of-sample prediction of cumulative long-term loan losses.[10] Accordingly, higher OVH indicates a greater delay in expected loss recognition. We run the following regression to examine the effect of OVH on banks' recovery lending:

$$\begin{aligned} RecoveryLending_{i,t} =& \beta_0 + \beta_1 * HurrExposure_{i,t} * OVH_{i,t} \\ & + \beta_2 * HurrExposure_{i,t} + \beta_3 * OVH_{i,t} + \gamma X_{i,h} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \end{aligned} \tag{7}$$

In addition, we investigate the effect of OVH on banks' post-hurricane long-term performance using the following regression:

$$\begin{aligned} Performance_{i,t} =& \beta_0 + \sum_{h=t-7}^{h=t-1} \beta_h Past1YrHurrExp_{i,h} * \Delta Loan_{i,h} * OVH_{i,h} \\ & + \sum_{h=t-7}^{h=t-1} Interactions_h + \gamma X_{i,t} + \alpha_i + \alpha_{s,t} + \epsilon_{i,t} \end{aligned} \tag{8}$$

$Interactions$ include two-way interactions between $Past1YrHurrExp$, $\Delta Loan$, and OVH, as well as each of the three individual terms. X includes bank characteristics that affect lending and performance measures. We also control for $ExpLoss$ and its interactions with $HurrExposure$ or $Past1YrHurrExp$ and $\Delta Loan$ to ensure that the effect of OVH is driven by loss overhang instead of expected future losses, following Lu and Nikolaev (2022). Bank

[10] Lu and Nikolaev (2022) show that the long-term forecasts of loan losses from the model achieve positive out-of-sample R^2 up to five years in the future, considerably outperforming long-term forecasts from other models.

fixed effects and state × year-quarter fixed effects control for time-invariant bank characteristics and state-level time trends that affect banks' lending and performance measures.

4 Data and sample

We construct the sample using data from several sources. Data on hurricane losses is acquired from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS provides county-level data on direct losses caused by natural disasters. This data includes information on the date of a hazard event, disaster type, affected location (county and state), and the dollar amount of property losses caused by the event in each county. The primary data source of SHELDUS is the Storm Data and Unusual Weather Phenomena provided by the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). Our sample includes property losses from all hurricanes recorded in SHELDUS. Since some events coded as "floods" are actually caused by hurricanes, we treat flood losses as hurricane losses when a flood event happens in a given county and other counties in the same state and quarter show a "hurricane" record.

Mortgage data is from the Home Mortgage Disclosure Act (HMDA) dataset. HMDA includes mortgage-level information on the lender, year, dollar amount, property location (down to the census tract level), type of purchaser (i.e., mortgage not sold or the type of purchaser if sold) of a mortgage, and variables related to loan prices. We use this data to construct bank-year-county-level measures of non-agency mortgage lending (i.e., mortgages originated and not sold by a bank). We also use the proportion of non-agency mortgages in a county calculated over the past three years to measure the bank's mortgage market share in that county. Small business loan data is from the Community Reinvestment Act (CRA) database. CRA includes loan-level information on the lender, year, dollar amount, and location (down to the county level). This dataset allows us to measure small business lending at the bank-year-county level.

Other bank accounting data is acquired from FR Y-9C reports. We measure balance sheet variables at the end of the fiscal period and annualize income statement items by summing the numbers in the current and preceding three quarters (that is, we use a four-quarter moving window to aggregate quarterly data). Flood insurance and FEMA assistant data are from the OpenFEMA dataset. SBA disaster loan data is from the SBA dataset. Variables related to expected losses and the timeliness of expected loss recognition are from Lu and Nikolaev (2022). To reduce the impact of extreme observations, we take log transformation or truncate top and bottom 1% observations for continuous variables. The final sample covers quarterly US bank holding companies' observations between 1994 and 2019.

Figures 1 and 2 provide descriptive evidence on the adverse and unpredictable nature of hurricane shocks. Figure 1, Panel A shows that Hurricanes and the related flooding contributed to the most property losses (over $331 billion) caused by natural disasters from 1990 to 2019. Panel B suggests that Over 5,800 hurricanes and related flooding events were recorded over the past 30 years. These events have the second highest per-event losses among all types of hazards, second only after the extremely rare earthquakes (Panel C). Figure 2 indicates that hurricanes can influence a wide range of areas in the US (Panel A and B), but the specific location of their landfalls and the corresponding damages in a year are random and vary considerably from year to year (Panel C).

Table 1 reports the descriptive statistics of variables used in our analysis. The mean and median of positive values of $HurrExposure$ are 0.00019. This means a bank's exposure to property losses from hurricanes (based on its mortgage market share in affected counties) is about 0.0002% of its total loans outstanding on average. While this number appears small, on average, it grows exponentially to at least 0.292% for the top 5% $HurrExposure$ (0.000264), which is greater than the median-level net charge-offs (0.18%) or loan loss provision (0.28%) in a year. Given a large number of positive $HurrExposure$ observations (over 10,000), there are over 500 bank-quarters that had top-5% $HurrExposure$ during the 26 years of our sample period. Figure 3 indicates that the log transformation in calculating $HurrExposure$

is effective in converting a highly right-skewed distribution to one that approximates the normal density. This specification follows prior studies (e.g., Cortés and Strahan, 2017) to mitigate a concern that the results are driven by the extreme tail. The average (median) loan losses are 0.33% (0.18%) of the average loan balance, and the average (median) allowance is around 4 (7) times of loan losses. The mean (median) OVH is around 1%. These summary statistics are similar to those documented in Lu and Nikolaev (2022) and suggest that banks are untimely in recognizing expected loan losses, on average.

5 Results

5.1 The effect of hurricane exposure on bank performance

Our baseline analysis examines banks' long-run performance following a hurricane. We follow the methodology discussed in Section 3.1. In Table 2, Panel A, we investigate the changes in net charge-offs and ROA in response to hurricane exposure while controlling for banks' characteristics, fixed effects, and state×year-quarter fixed effects. As reported in column 1, hurricane exposure significantly reduces banks' loan losses in the first two years following the shock. However, loan losses return to the pre-hurricane level by the third year, then surge above the pre-hurricane level five to six years after the shock. The economic magnitude of hurricanes' impact is significant. An average (median)-level hurricane exposure leads to around 0.025 percentage point decrease in net charge-offs in the first two years, which accounts for 7% (14%) of average (median) net charge-offs. In contrast, an average (median) hurricane exposure leads to about 0.021 percentage point increase in net charge-offs, or 6% (12%) of average (median) net charge-offs, in the fifth to sixth year. In column 2, we observe a similar pattern in the case of profitability. ROA increases significantly in the first two years after a hurricane shock before declining in the sixth and seventh years. The documented patterns are surprising, as they suggest that banks perform better after a hurricane shock and only after some time performance reverses.

Do banks incorporate the documented long-term losses into their risk assessment in a timely manner?[11] To answer this, we examine how banks' loan loss provisions and allowances respond to hurricanes. The results are reported in columns 3-4 of Table 2, Panel A. Similar to loan losses, loan loss provision and allowance decline in the first two years after a hurricane shock before increasing in the fourth and fifth years. This pattern suggests that banks are not timely in incorporating hurricane losses immediately after the shock and only increase provisioning when loan losses start to pick up in the longer term.

One potential concern with the above specification is that losses are correlated over time, thus leading to potential multicollinearity issues when we simultaneously include seven lagged variables and making the interpretations more challenging. We address this in Panel B of Table 2. Instead of pooling all lags of hurricane exposure measures in one regression, we include one lag at a time and thus run seven separate regressions before reporting the estimates. Control variables are as of the year of hurricane exposure. Each column in Panel B reports the results (each regression coefficient comes from a unique regression). The results are closely in line with those in Panel A, and hence, the documented performance reversals are not driven by the issues related to collinearity.

The unusual patterns of post-hurricane bank performance are important to understand because they suggest that the negative impact of hurricanes on banks is of a long-term nature and that banks enjoy a "buffer period" in the short term, during which they have the opportunity to provision for long-term losses without the pressure from heightened loan losses. However, we also find that banks do not use the buffer period to ramp up loan loss reserves. Insufficient provisioning in the short term could give banks the incentives and opportunities to increase risk-taking, undermining their long-term resilience to hurricanes.

Extreme and unexpected events. Climate hazards threaten banks the most when they

[11]Note that while banks follow the incurred-loss model during the sample period, it is still meaningful to examine their recognition of long-term losses. This is because banks have considerable discretion in recognizing incurred losses (Ryan, 2012, 2017) and because their allowance on average covers multiple years of charge-offs, which suggests that banks reserve significant buffer against long-term losses (Lu and Nikolaev, 2022).

cause extreme or unexpected damages, and a key concern about banks' climate risk is the potential that banks will be exposed to more severe and unexpected climate hazards in the future because of climate change. Indeed, climate models predict that hurricanes will likely cause more intense damage and expand into less expected areas due to climate change (Knutson, Chung, Vecchi, Sun, Hsieh, and Smith, 2021; Studholme, Fedorov, Gulev, Emanuel, and Hodges, 2022). Therefore, it is important to know whether the documented effect of hurricanes on banks remains or even intensifies when hurricanes cause more extreme losses or hit less expected regions.

To address this question, we measure banks' exposure to extreme hurricanes that caused losses in the 95th percentile, $ExtrmHurrExposure$, and banks' exposure to hurricane landfalls in unexpected regions (i.e., counties that experienced no more than two hurricanes in the sample period), $UnexpHurrExposure$. We run the same regressions as those in Panel A of Table 2, replacing $HurrExposure$ with the two new exposure measures. We find that more extreme and unexpected hurricanes have more pronounced effects on bank performance, especially in the long term. As reported in Table 3, most of the coefficients of $ExtrmHurrExposure$ and $UnexpHurrExposure$ have the same signs and greater magnitude than those of $HurrExposure$ in Table 2, Panel A. More importantly, the magnitude of hurricanes' long-term negative impact increases much more than their short-term positive effect when hurricanes become more extreme or hit less expected regions. For example, when regressing NCO on hurricane exposures, the coefficients for the first two years decrease slightly from around -1.3 on average for all hurricanes to -1.6 (-1.7) on average for extreme (unexpected) hurricanes. However, the coefficients for the fifth and sixth year jump from around 1.1 on average for all hurricanes to 2.9 (1.8) on average for extreme (unexpected) hurricanes. Therefore, with the continued change in climate, the documented pattern is likely to be an even more important channel underlying hurricanes' impact on banks in the future.

5.2 Channels underlying hurricanes' effect on banks

After documenting the patterns of post-hurricane bank performance, we explore specific channels contributing to these patterns. We start by examining the role of governmental disaster aid.

5.2.1 Disaster aid channel

We follow the methodology laid out in Section 3.2.1 to test the role of financial aid in explaining the documented bank performance patterns. Specifically, we exploit exogenous variation in banks' exposure to hurricane-related flood insurance payments ($FloodInsurance$).

Table 4 reports the results. Consistent with the prediction that disaster assistance indirectly helps banks reduce loan losses, we find that banks exposed to counties that receive flood insurance payments report significantly lower net charge-offs and higher ROA in the first two years after experiencing a hurricane shock. More interestingly, the presence of financial aid induces higher long-term losses. In addition, flood insurance coverage contributes to banks' reduced (increased) loan loss provisions in the short (long) run after hurricanes. These results suggest that while the government's disaster relief helps bank performance in the short term, it leads to banks' underestimation of credit risk and potentially to increased risk-taking.

Our additional analysis, reported in Table A1 of the Online Appendix, suggests that SBA disaster loans or FEMA grants, both of which are endogenously determined, do not change hurricanes' short-term impact on loan losses. These results are consistent with Billings, Gallagher, and Ricketts (2022)'s finding that flood insurance is more effective than SBA disaster loans or FEMA grants in providing support to disaster victims facing financial difficulties. This is because SBA disaster loans and FEMA grants are more likely to cover wealthier households. At the same time, flood insurance coverage is randomly determined by the extent to which a hurricane affects floodplains.

5.2.2 Risk-taking channel

Next, we investigate whether increased risk-taking after hurricanes can, in part, explain banks' deteriorated long-term performance. We follow the methodology laid out in Section 3.2.2. Specifically, we investigate whether banks' lending becomes riskier following hurricane exposure.

First, we examine whether a bank's lending immediately following hurricane exposures triggers higher losses in the longer run. For each quarter, we measure banks' total hurricane exposure in the previous four quarters, $Past1YrHurrExp$, by summing the $HurrExposure$ in these quarters. Then, we regress bank performance on the interactions of $Past1YrHurrExp$ and loan growth, $\Delta Loan$, for each of the past seven years. The coefficients of these interaction terms reveal how hurricane exposure in the past year affects future bank performance through its impact on the quality of lending in the current quarter.

As reported in Table 5, we find that lending in the year after hurricane exposure translates into significantly higher loan losses and reduces ROA two to five years in the future (columns 1 and 2). These results support the prediction that banks increase risk-taking in the short term after experiencing hurricanes (e.g., due to financial aid and laxer reporting environment). In addition, we find that banks do not reflect the increased risk-taking in their provisions until two years later, when loan losses begin to be realized (columns 3 and 4).

Next, we zoom in on banks' lending behavior in the short term after hurricane exposures to examine how exactly banks increase their risk-taking. To do so, we focus on banks' "recovery lending," i.e., mortgage or small business lending to hurricane-affected counties. Table 6, Panel A, reports the results using bank-year-level regressions. We find that hurricane exposure significantly increases mortgage and small business lending to the affected counties in the year of the hurricane shock and the following year. In addition, the affected banks' mortgage prices increase significantly in the year following the hurricane shock. On the contrary, hurricane exposure has an insignificant or negative impact on lending to regions unaffected by hurricanes, as reported in Panel B of Table 6.

To further tighten identification, we use bank-county-year-level data to examine the impact of hurricane exposure on lending. As reported in Table 6, Panel C, we find the consistent result that hurricane-affected bank-counties experience significant increases in mortgage and small business lending and higher mortgage prices. Overall, the results in Tables 5 and 6 suggest that hurricane-affected banks increase their risk-taking by shifting lending to the riskier hurricane-affected counties.

5.2.3 Financial reporting channel

Finally, we explore whether banks' financial reporting practices related to loan forbearance and delayed loan loss recognition explain banks' post-hurricane performance. To test the forbearance explanation, we examine how hurricanes affect banks' loan delinquency (i.e., past-due) status and nonaccrual loans, as discussed in Section 3.2.3.

As reported in the first two columns of Table 7, hurricane exposure has an insignificant effect on the proportion of loans that are either more than 90 days past due or 30-90 days past due. This result is inconsistent with the forbearance contributing to lower loan losses and higher profitability two years after hurricanes. One potential reason for this result is that deferral programs typically last up to one year, and borrowers tend to repay early. For example, the use of forbearance sharply increased in the first three months after Hurricane Harvey before dropping back to the pre-hurricane level in the twelfth month (Del Valle, Scharlemann, and Shore, 2022). Therefore, the effect of forbearance may be too short-lived to explain bank performance in the two years after hurricane exposures. We also find that nonaccrual loans decline significantly in the first two years after hurricanes, as indicated in the last column of Table 7. This suggests that borrowers' repayment ability indeed improves in the short term after hurricanes. Therefore, the decline in loan losses in the short term after hurricanes is more likely driven by the improved ability to meet payment obligations in the short term, consistent with the injections of financial aid, rather than accounting for loan forbearance.

In our analysis reported in Table 2 and discussed in Section 5.1, we documented that loan loss provisions and allowances for loan losses are not timely enough to capture long-term losses after hurricanes. To further test the role of delayed loan loss recognition in driving post-hurricane bank performance, we investigate whether the delayed loan loss recognition amplifies the effect of hurricanes on banks' risk-taking and long-term loan losses. As discussed in Section 3.2.3, we use the expected loss overhang, OVH, developed by Lu and Nikolaev (2022) as a proxy for (cross-sectional) delays in expected loss recognition at the bank-quarter level.

We first examine whether the delayed recognition of long-term loan losses contributes to hurricanes' positive effect on recovery lending. As reported in the first two columns of Table 8, after experiencing hurricanes, banks that are slower in recognizing long-term losses also exhibit a greater shift in mortgage and small business lending to hurricane-affected counties. In addition, delaying banks charge higher mortgage interest rates, also indicating that these banks lend to riskier borrowers (column 4).

While delaying expected loss recognition is associated with riskier lending in hurricane-affected regions, it does not appear to affect total lending or lending in regions unaffected by hurricanes, as indicated in columns 5 to 7. These results line up with our prediction that delayed loan loss provisioning contributes to banks' risk-taking behavior following a hurricane.

Finally, we investigate the role of delayed loan loss recognition in banks' long-term performance. If reporting delays lead to riskier loan portfolios, this should amplify the documented (in Table 5) negative effect of lending immediately following a hurricane on banks' long-term performance. To test this prediction, we regress bank performance measures on the triple interactions between $Past1YrHurrExp$, $\Delta Loan$, and OVH for the previous seven years.

As reported in Table 9, delayed loan loss recognition significantly enhances the effects of post-hurricane lending in increasing loan losses, reducing ROA, and increasing loan loss provision three to seven years in the future. Overall, these results support the prediction that delayed loan loss recognition contributes to banks' short-term risk-taking and long-term underperformance after hurricanes.

6 Conclusion

As global central bankers are increasingly concerned about the effects of climate risks on the financial system, understanding the impact of extreme climate hazards on banks' performance, especially the transmission channels involved, is of considerable importance. We shed light on this by examining the long-run effect of extreme weather events, hurricanes, on bank loan losses and their profitability.

Our findings reveal an unexpected pattern in banks' performance following a hurricane. We find that banks' hurricane exposure leads to reduced loan losses and increased profitability in the first two years. However, these trends reverse, and bank performance deteriorates in the longer term. When hurricanes are more severe or unexpected, they lead to even greater long-term losses relative to their positive short-term effect. Moreover, despite the higher loan losses in the long term after hurricanes, banks do not recognize these losses in a timely manner.

We examine several possible explanations for these findings. First, we show that governmental disaster aid, flood insurance in particular, contributes to banks' strong performance in the short term after hurricanes but also leads to increased losses in the longer run, which points to increased risk-taking. Second, we show that banks exposed to hurricanes issue riskier loans and shift lending to the riskier (hurricane-affected) regions. This leads to increased loan losses and reduced profitability in the long term. Finally, delayed expected loss recognition facilitates banks' risk-taking after hurricanes and amplifies hurricanes' effect on banks' long-term loan losses.

Our paper has several policy implications for regulators concerned about banks' climate risks. First, banks' long-term losses following hurricanes are at least partly driven by banks' response to these events, i.e., taking new risks in response to the hurricanes. Increased risk-taking is more pronounced among banks that exhibit delayed recognition of long-term loan losses, suggesting that a lax reporting environment is potentially an important driver in determining banks' post-hurricane response. These findings suggest that monitoring and disciplining banks' risk-taking and loss recognition *after* climate hazards could be an effective way to assess and control banks' exposure to climate risks. Second, governmental aid to disaster victims indirectly strengthens banks' performance in the periods that immediately follow the climate hazards. This creates a positive externality associated with governmental disaster assistance that was not understood previously. Finally, hurricane-affected banks take on more risks by shifting lending to hurricane-affected regions. While this response can lead to long-term bank losses, it provides important financial support to hurricane victims. Policymakers need to consider both effects and balance maintaining financial stability and supporting disaster recovery.

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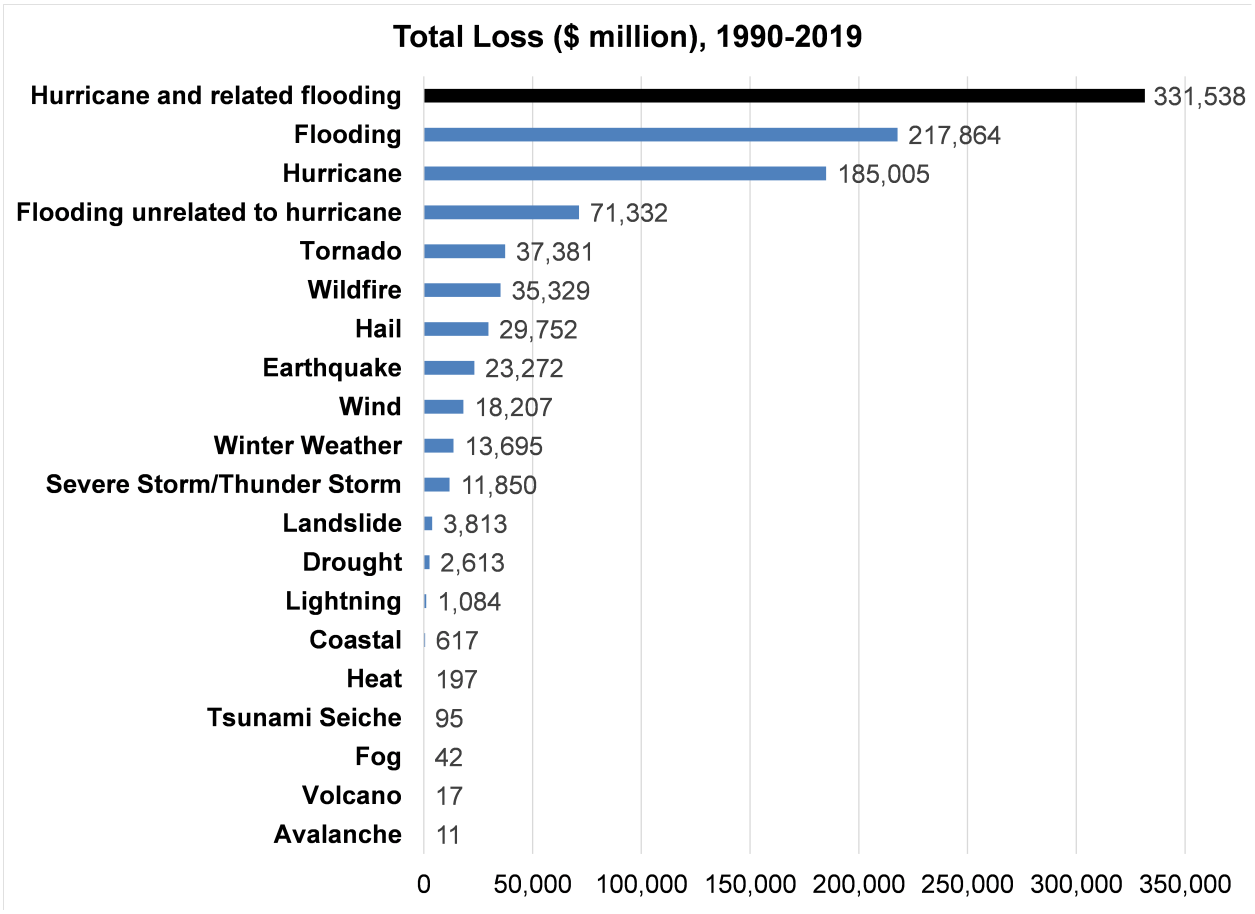
Figures

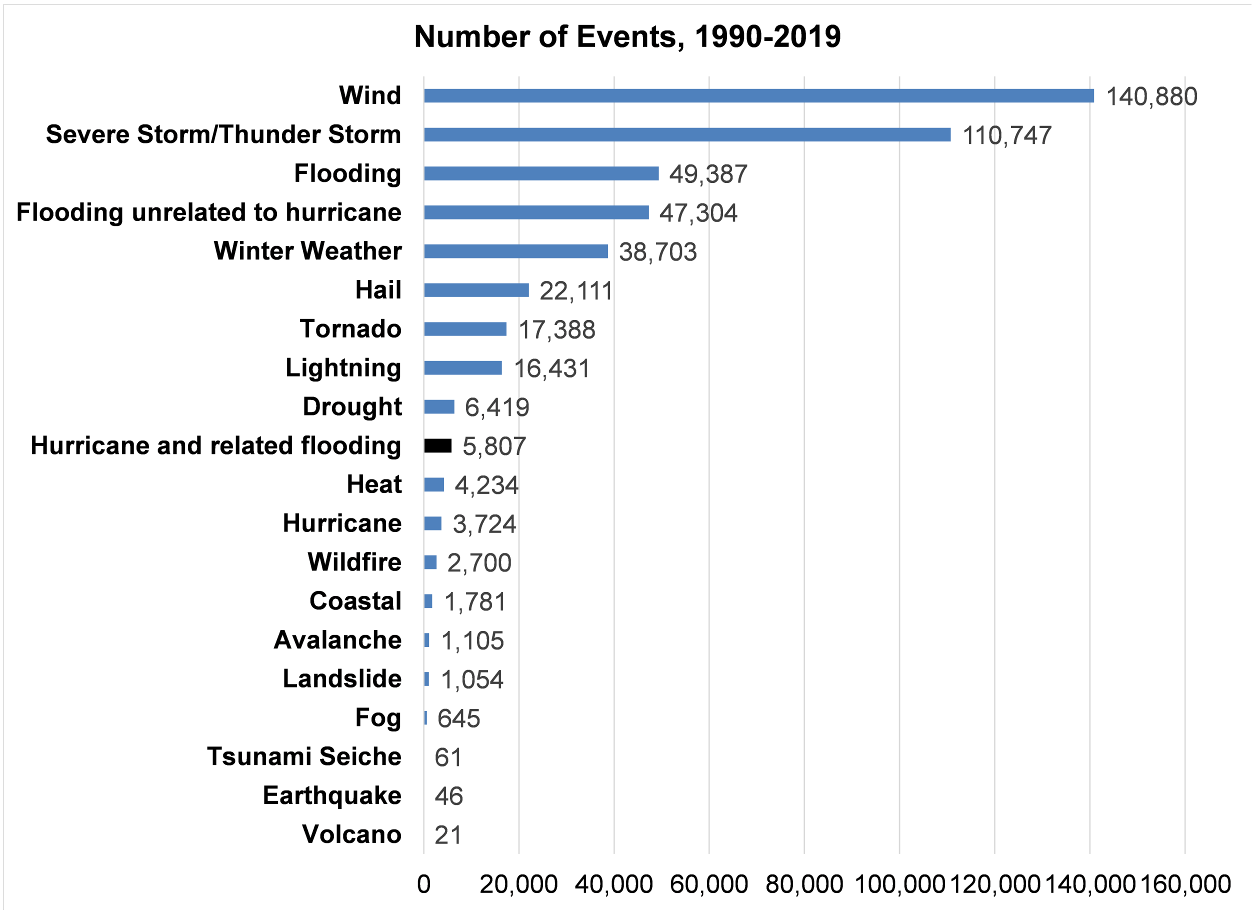
Figure 1: Damage, frequency, and intensity of natural disasters by type.

These figures plot the damage, frequency, and intensity of natural disasters by disaster type from 1990 to 2019 in the US. Damage is the dollar amount of property losses caused by natural disasters. Frequency is the number of natural disaster events. Intensity is the ratio of damage to frequency. Natural disaster data is from the SHELDUS dataset.

Panel A. Total damage of natural disasters by type.



Panel B. Frequency of natural disasters by type.



Panel C. Per event damage of natural disasters by type.

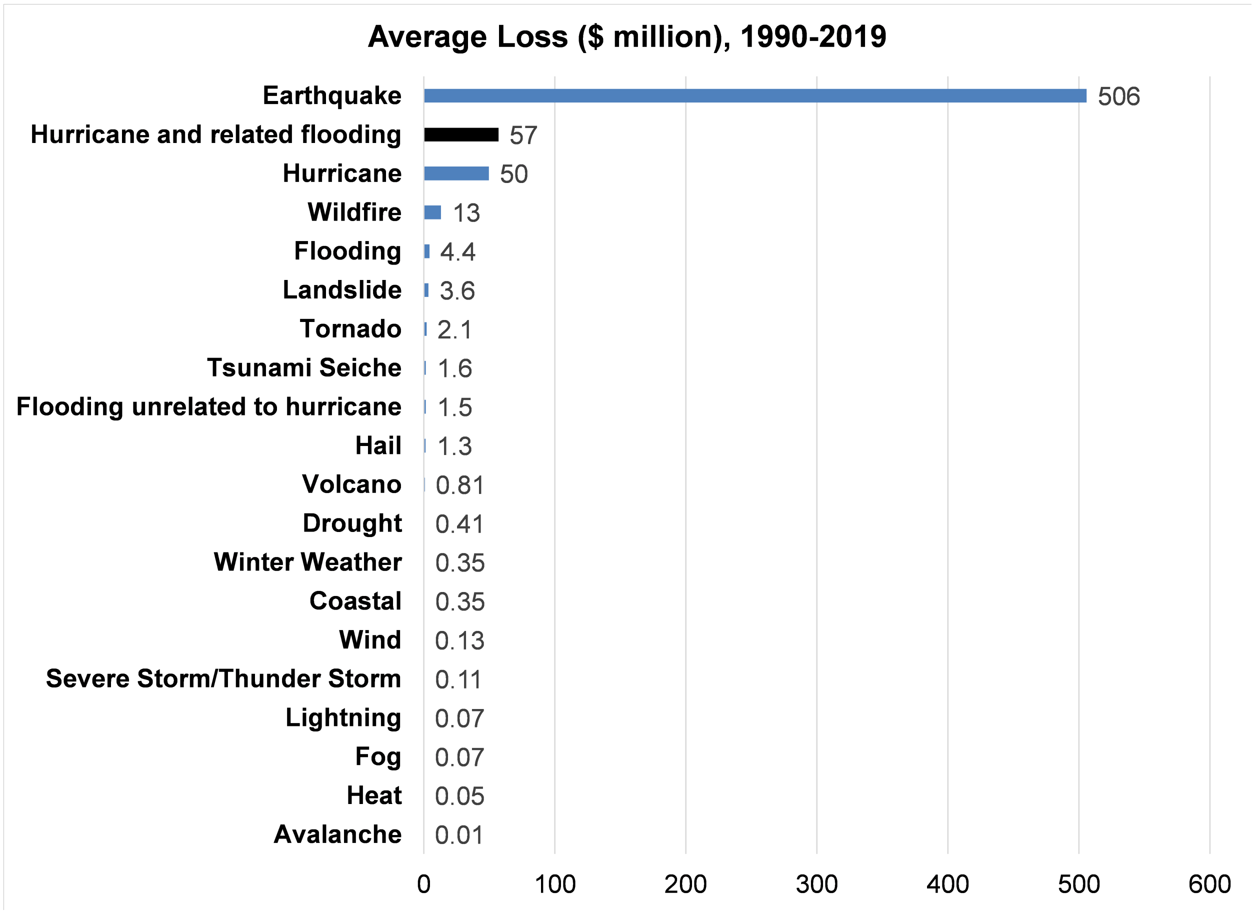
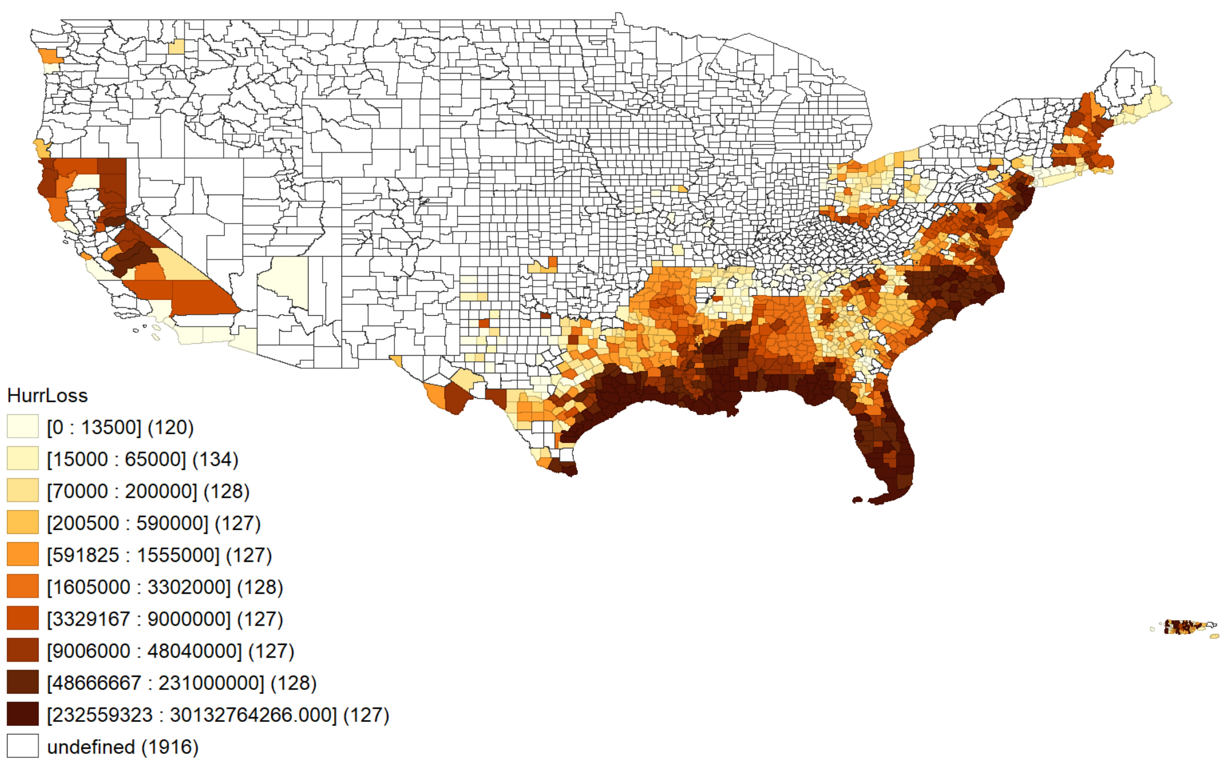


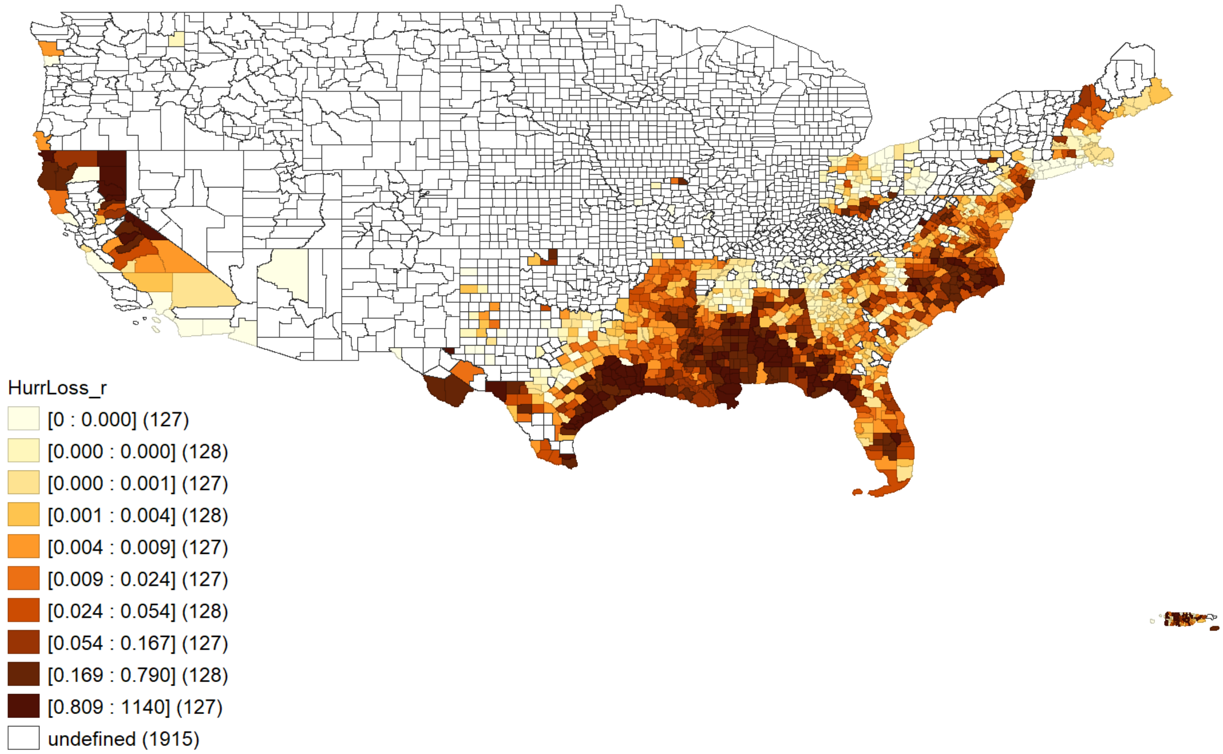
Figure 2: Geographical distribution of hurricane losses.

These figures map the total hurricane damage and the average ratio of hurricane damage to the last three years' mortgages from 1990 to 2019 in the US at the county level. Hurricane damage is the dollar amount of property losses caused by hurricanes and hurricane-related flooding. White areas on the map are counties without any hurricane damage record in the sample period. Counties with at least one hurricane damage record are color-coded based on the quintile of damage. Darker areas have greater hurricane damage. Hurricane data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset.

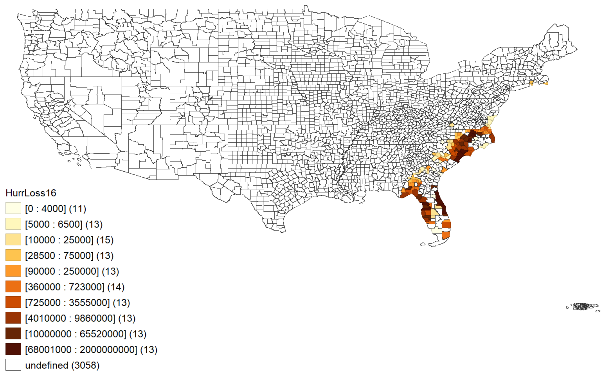
Panel A. Total dollar amount of hurricane damage.



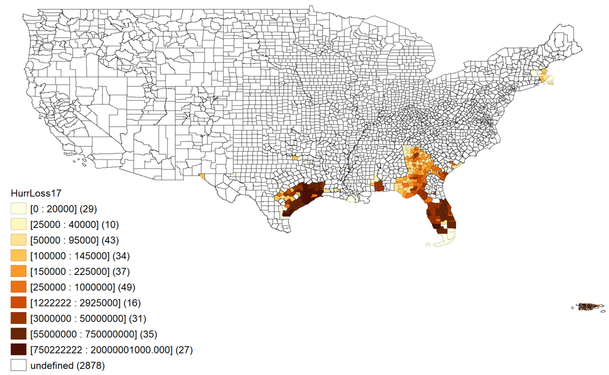
Panel B. Average ratio of hurricane damage to last three years' mortgage.



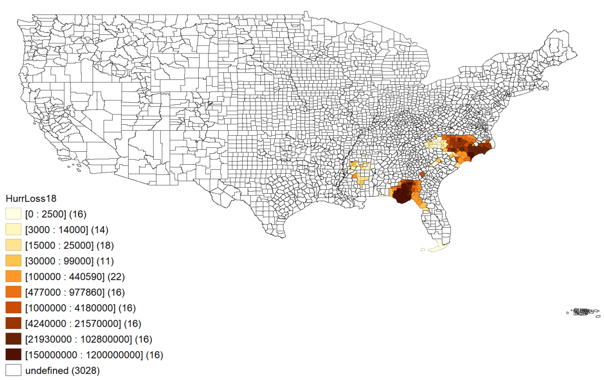
Panel C. Dollar amounts of hurricane damage in each year during 2016-2019.



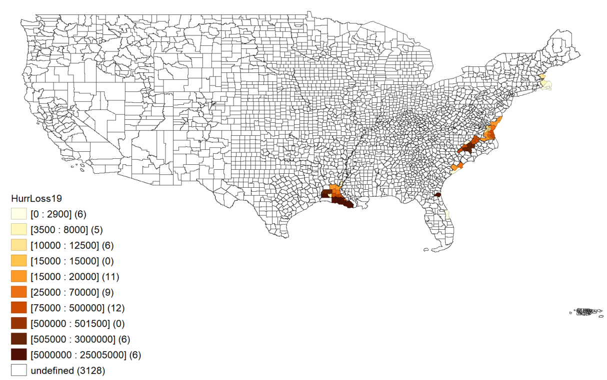
2016



2017



2018

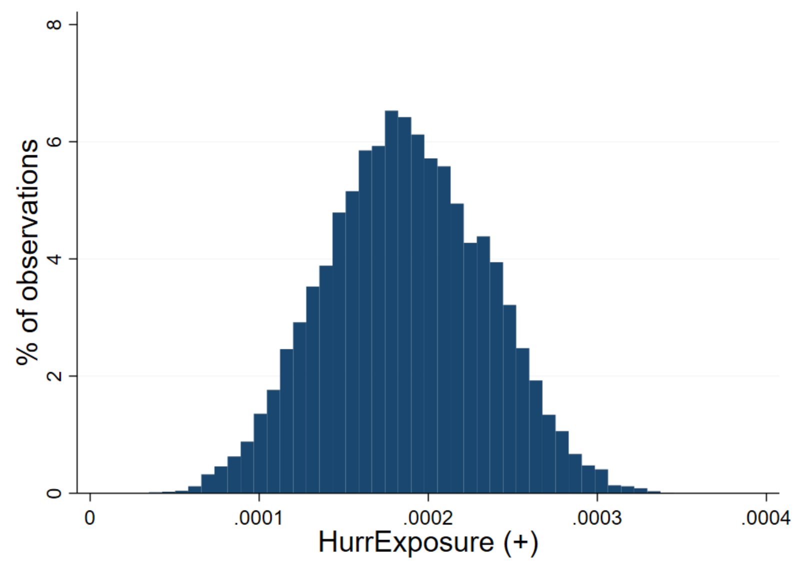


2019

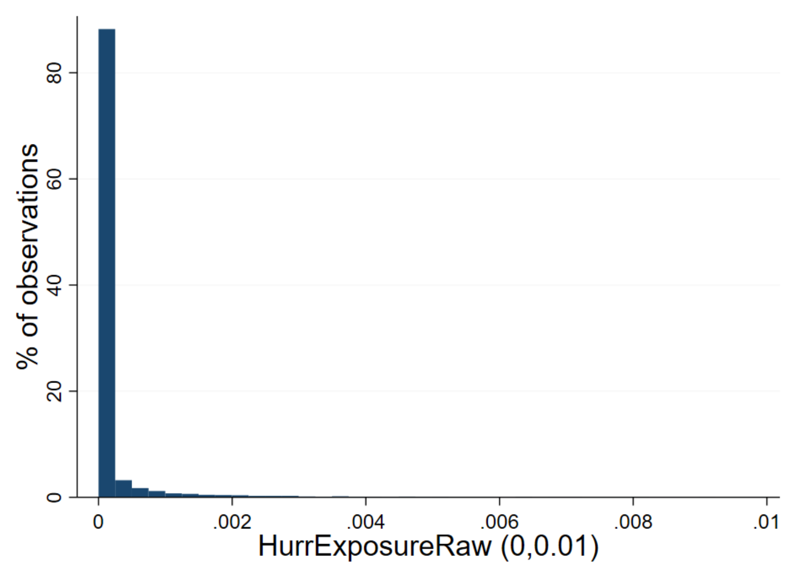
Figure 3: Distribution of hurricane exposure measures.

These figures plot the distribution of positive $HurrExposure$ and $HurrExposureRaw$ within (0,0.01). $HurrExposure$ is the measure of a bank's hurricane exposure, as defined in Equation 2. $HurrExposureRaw$ is $HurrExposure$ before taking the log transformation.

Panel A. Distribution of positive $HurrExposure$



Panel B. Distribution of $HurrExposureRaw$ within (0,0.01).



Tables

Table 1: Descriptive statistics.

$HurrExposure(+)$ is the positive value of the exposure to hurricane damage, as defined in Equation 2. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $FloodInsurance$ is an indicator variable equal to one if at least one of the hurricane-affected counties that the bank is exposed to received hurricane-related flood insurance payment, and zero otherwise. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. $PastDue\_over90$ ($PastDue\_30to89$) is loans that are past due 90 days or more (30 through 89 days) and still accruing scaled by total loans outstanding. $Nonaccrual$ is nonaccrual loans scaled by total loans outstanding. OVH is expected loss overhang, which is the excess of expected loan loss over ALL from Lu and Nikolaev (2022). $Size$ is the natural log of total assets. $RELoans$ is the proportion of real estate loans. $ConsLoans$ is the proportion of consumer loans. $Tier1Ratio$ is the Tier 1 capital ratio. $FloatRatio$ is the percentage of loans that reprice or mature within one year. $LoansYield$ is the annualized tax-equivalent interest rate on loans. The sample covers quarterly US-bank-holding companies' observations between 1994 and 2019. Income statement items are annualized by summing the numbers in the current and preceding three quarters. Hurricane damage data is from SHELDUS. Bank mortgage data is from the HMDA data. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Flood insurance and FEMA assistant data is from the OpenFEMA Dataset. SBA disaster loan data is from the SBA dataset.

	Count	Mean	SD	P5	P25	P50	P75	P95
HurrExposure (+)	10073	0.00019	0.00005	0.00011	0.00015	0.00019	0.00022	0.00026
NCO	84539	0.00334	0.00470	-0.00010	0.00065	0.00181	0.00404	0.01300
ROA	84539	0.03217	0.01485	0.00980	0.02038	0.03202	0.04426	0.05498
LLP	84539	0.00424	0.00515	0.00000	0.00142	0.00282	0.00510	0.01448
ALL	84539	0.01463	0.00534	0.00793	0.01128	0.01368	0.01678	0.02487
FloodInsurance	84539	0.05709	0.23201	0.00000	0.00000	0.00000	0.00000	1.00000
ΔLoan	84539	0.10648	0.13542	-0.06788	0.02709	0.08639	0.16039	0.35297
PastDue_Over90	84539	0.00151	0.00240	0.00000	0.00001	0.00050	0.00194	0.00655
PastDue_30to89	84539	0.00672	0.00773	0.00000	0.00033	0.00446	0.00984	0.02256
Nonaccrual	84539	0.00962	0.01200	0.00019	0.00242	0.00557	0.01173	0.03459
OVH	33816	0.01018	0.00973	-0.00480	0.00446	0.00964	0.01517	0.02805
Size	84539	13.69069	1.36372	12.14813	12.69179	13.41273	14.24967	16.39529
ReLoan	84539	0.71273	0.15572	0.42776	0.61900	0.73277	0.82772	0.93324
ConsLoans	84539	0.07701	0.07906	0.00325	0.01937	0.05046	0.10908	0.23815
Tier1Ratio	84539	0.13122	0.04263	0.08050	0.10405	0.12249	0.14812	0.21366
FloatRatio	84539	0.38115	0.15855	0.14609	0.26366	0.36938	0.48485	0.66162
LoansYield	84539	0.07297	0.01888	0.04566	0.05813	0.07104	0.08746	0.10429

Table 2: The effect of hurricanes on loan losses, profitability, and loan loss recognition.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on hurricane exposures in the past seven years. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. In Panel A, each column reports the results of one regression, which includes the $HurrExposure$'s in the past seven years. In Panel B, each column reports the results of seven regressions. Each regression coefficient in each column is estimated by regressing the dependent variable on one of the $HurrExposure$'s in the past seven years, with controls measured in the same year as $HurrExposure$. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website for the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Panel A. Including all the seven lags of $HurrExposure$ in each regression.

	(1)	(2)	(3)	(4)
VARIABLES	NCO_t	ROA_t	LLP_t	ALL_t
$HurrExposure_{t-1}$	-1.121***	2.500***	-1.447***	-1.044**
	(-2.720)	(3.793)	(-3.115)	(-2.481)
$HurrExposure_{t-2}$	-1.497***	2.527***	-1.590***	-0.950**
	(-3.690)	(3.956)	(-3.539)	(-2.411)
$HurrExposure_{t-3}$	-0.296	-0.507	0.649	0.183
	(-0.677)	(-0.736)	(1.200)	(0.417)
$HurrExposure_{t-4}$	0.454	0.933	1.428**	0.314
	(0.988)	(1.134)	(2.513)	(0.739)
$HurrExposure_{t-5}$	0.996**	-0.859	1.214**	1.414***
	(2.038)	(-1.162)	(2.384)	(3.350)
$HurrExposure_{t-6}$	1.214**	-1.647**	-0.0821	0.658
	(2.564)	(-2.040)	(-0.159)	(1.448)
$HurrExposure_{t-7}$	0.593	-1.481**	-0.232	-0.302
	(1.180)	(-2.004)	(-0.411)	(-0.594)
Observations	46,354	46,354	46,354	46,354
Adjusted R-squared	0.580	0.852	0.576	0.665
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Including one lag of *HurrExposure* at a time in each regression.

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$HurrExposure_{t-1}$	-1.387***	2.264***	-1.557***	-1.178***
	(-3.310)	(3.499)	(-3.375)	(-2.618)
$HurrExposure_{t-2}$	-1.897***	2.505***	-1.516***	-1.355***
	(-4.466)	(3.647)	(-3.327)	(-2.744)
$HurrExposure_{t-3}$	-0.574	-0.425	0.642	-0.342
	(-1.279)	(-0.547)	(1.170)	(-0.634)
$HurrExposure_{t-4}$	0.655	0.150	1.806***	0.171
	(1.373)	(0.168)	(3.085)	(0.329)
$HurrExposure_{t-5}$	1.158**	-0.655	1.638***	1.044**
	(2.221)	(-0.784)	(2.945)	(2.037)
$HurrExposure_{t-6}$	1.452***	-1.143	0.458	0.331
	(2.738)	(-1.222)	(0.788)	(0.603)
$HurrExposure_{t-7}$	1.364**	-1.830**	0.786	-0.139
	(2.537)	(-2.067)	(1.352)	(-0.237)
Observations	35,946-45,884	35,946-45,884	35,946-45,884	35,946-45,884
Adjusted R-squared	0.578-0.585	0.789-0.847	0.572-0.582	0.662-0.678
$Controls_{t-h}$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Table 3: The effect of extreme and unexpected hurricanes on bank performance.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on the exposure to extreme or unexpected hurricanes. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current year, and those lagged by one year. $ExtrmHurrExposure$ is the exposure to extreme hurricanes that caused losses in the 95th percentile. $UnexpHurrExposure$ is the exposure to hurricanes in unexpected regions, i.e., counties that experienced no more than 2 hurricanes in the sample period. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$ in the current year, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Panel A. Extreme hurricanes

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$ExtrmHurrExposure_{t-1}$	-2.095***	4.020***	-2.625***	-1.652***
	(-4.012)	(3.925)	(-3.940)	(-2.764)
$ExtrmHurrExposure_{t-2}$	-1.325**	1.493	-0.0624	-0.453
	(-2.005)	(1.279)	(-0.0883)	(-0.733)
$ExtrmHurrExposure_{t-3}$	0.582	-3.184*	2.074*	1.574**
	(0.649)	(-1.915)	(1.908)	(2.100)
$ExtrmHurrExposure_{t-4}$	2.916***	-2.478	4.975***	1.509
	(2.877)	(-1.274)	(3.718)	(1.627)
$ExtrmHurrExposure_{t-5}$	3.572***	-1.673	4.461***	3.367***
	(2.827)	(-1.002)	(3.432)	(3.268)
$ExtrmHurrExposure_{t-6}$	2.156*	-2.578*	-0.0118	2.552**
	(1.747)	(-1.650)	(-0.00931)	(2.366)
$ExtrmHurrExposure_{t-7}$	1.268	0.174	-3.489***	-0.620
	(1.147)	(0.118)	(-3.063)	(-0.562)
Observations	46,354	46,354	46,354	46,354
Adjusted R-squared	0.580	0.852	0.576	0.665
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Unexpected hurricanes

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$UnexpHurrExposure_{t-1}$	-1.314	1.760	-1.420	-0.259
	(-1.628)	(1.480)	(-1.594)	(-0.367)
$UnexpHurrExposure_{t-2}$	-1.161*	3.135***	-2.142***	-1.115*
	(-1.737)	(2.717)	(-2.800)	(-1.750)
$UnexpHurrExposure_{t-3}$	-0.698	3.143***	-0.989	-1.071
	(-0.944)	(3.006)	(-1.096)	(-1.452)
$UnexpHurrExposure_{t-4}$	-1.308*	2.053**	-0.243	-1.131
	(-1.877)	(1.966)	(-0.281)	(-1.573)
$UnexpHurrExposure_{t-5}$	1.444**	-3.185***	2.804***	0.114
	(2.014)	(-2.645)	(3.394)	(0.187)
$UnexpHurrExposure_{t-6}$	2.107***	-3.922***	1.362	0.149
	(2.827)	(-3.188)	(1.510)	(0.210)
$UnexpHurrExposure_{t-7}$	-0.273	-2.017*	-0.532	0.809
	(-0.349)	(-1.820)	(-0.582)	(1.069)
Observations	46,354	46,354	46,354	46,354
Adjusted R-squared	0.579	0.852	0.576	0.664
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Table 4: The effect of flood insurance payments on loan losses, profitability, and loan loss recognition after hurricanes.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on the interactions of hurricane exposure and the exposure to flood insurance payments in the past seven years. *NCO* is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. *ROA* is the sum of pre-tax income and interest expense scaled by the book value of assets. *LLP* is loan loss provision scaled by the average loan balance. *ALL* is allowance for loan losses scaled by the average loan balance. *HurrExposure* is the exposure to hurricane damage, as defined in Equation 2. *FloodInsurance* is an indicator variable equal to one if at least one of the hurricane-affected counties that the bank is exposed to received hurricane-related flood insurance payment and zero otherwise. *Controls* include *Size*, *RELoans*, *ConsLoans*, *Tier1Ratio*, *FloatRatio*, and *LoansYield*, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\mathrm{NCO_t}$	(2) $\mathrm{ROA_t}$	(3) $\mathrm{LLP_t}$	(4) $\mathrm{ALL_t}$
$\mathrm{HurrExposure_{t\text{-}1} * FloodInsurance_{t\text{-}1}}$	-3.294**	6.776***	-3.684*	-2.774*
	(-2.109)	(2.796)	(-1.880)	(-1.810)
$\mathrm{HurrExposure_{t\text{-}2} * FloodInsurance_{t\text{-}2}}$	-3.596**	5.607**	-3.054*	-3.100*
	(-2.256)	(1.962)	(-1.663)	(-1.820)
$\mathrm{HurrExposure_{t\text{-}3} * FloodInsurance_{t\text{-}3}}$	-0.629	-0.566	-2.134	-1.568
	(-0.329)	(-0.160)	(-0.914)	(-0.891)
$\mathrm{HurrExposure_{t\text{-}4} * FloodInsurance_{t\text{-}4}}$	2.166	2.628	4.405	-2.969
	(0.946)	(0.761)	(1.631)	(-1.346)
$\mathrm{HurrExposure_{t\text{-}5} * FloodInsurance_{t\text{-}5}}$	3.865	-1.623	7.642***	-0.176
	(1.592)	(-0.470)	(2.680)	(-0.0788)
$\mathrm{HurrExposure_{t\text{-}6} * FloodInsurance_{t\text{-}6}}$	1.076	1.423	2.016	2.618
	(0.450)	(0.380)	(0.777)	(1.222)
$\mathrm{HurrExposure_{t\text{-}7} * FloodInsurance_{t\text{-}7}}$	4.451*	-1.149	-0.295	-0.516
	(1.889)	(-0.372)	(-0.118)	(-0.225)
Observations	46,354	46,354	46,354	46,354
Adjusted R-squared	0.580	0.852	0.576	0.665
$\mathrm{HurrExposure_{t\text{-}1\ -\ t\text{-}7}}$	Yes	Yes	Yes	Yes
$\mathrm{FloodInsurance_{t\text{-}1\ -\ t\text{-}7}}$	Yes	Yes	Yes	Yes
$\mathrm{Controls_t}$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Table 5: Lending after hurricanes and long-term loan losses, profitability, and loan loss recognition.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on the interactions of loan growth and cumulative hurricane exposure in the past four quarters for each of the previous seven years. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. $Past1YrHurrExp$ is the sum of $HurrExposure$ over the past four quarters. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$Past1YrHurrExp_{t-1} * \Delta Loan_{t-1}$	2.959	-0.592	-0.794	1.768
	(1.620)	(-0.204)	(-0.393)	(0.893)
$Past1YrHurrExp_{t-2} * \Delta Loan_{t-2}$	4.374**	-5.774*	5.664**	4.529**
	(2.510)	(-1.941)	(2.367)	(2.121)
$Past1YrHurrExp_{t-3} * \Delta Loan_{t-3}$	7.863***	-14.86***	9.303***	6.524***
	(3.480)	(-4.006)	(3.486)	(2.910)
$Past1YrHurrExp_{t-4} * \Delta Loan_{t-4}$	4.332**	-7.706**	5.799**	5.975***
	(2.235)	(-2.406)	(2.575)	(2.827)
$Past1YrHurrExp_{t-5} * \Delta Loan_{t-5}$	4.992***	-7.943***	4.501**	6.381***
	(2.747)	(-2.837)	(2.164)	(3.306)
$Past1YrHurrExp_{t-6} * \Delta Loan_{t-6}$	0.449	3.574	-2.805	4.800**
	(0.225)	(1.231)	(-1.193)	(2.295)
$Past1YrHurrExp_{t-7} * \Delta Loan_{t-7}$	2.473	2.633	0.199	3.404
	(1.293)	(0.777)	(0.0951)	(1.635)
Observations	39,529	39,529	39,529	39,529
Adjusted R-squared	0.609	0.843	0.597	0.701
$Past1YrHurrExp_{t-1\ -\ t-7}$	Yes	Yes	Yes	Yes
$\Delta Loan_{t-1\ -\ t-7}$	Yes	Yes	Yes	Yes
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Table 6: Lending in the short term after hurricanes

Panel A. Recovery lending

This table reports estimates from the bank-year-level OLS regressions of recovery lending and mortgage prices on hurricane exposures. $\Delta MortgRec$ ($\Delta SBLRec$) is recovery mortgage (small business) lending, which is non-agency mortgages (small business loans) issued to counties that experienced hurricanes in the current year (for columns 1 and 2) or the previous year (for columns 5 and 6) minus mortgages (small business loans) issued to the same counties a year before the hurricane year, scaled by lagged total loans outstanding. $ShareRec$ ($SpreadRec$) is the $Share$ ($Spread$) of recovery mortgage lending. $Share$ is the proportion of mortgages issued with a positive spread over 3% plus the yield on Treasury securities of comparable maturity. $Spread$ is the average spread of mortgages with a positive spread. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage (small business loan) data is from the HMDA (CRA) dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\Delta \mathrm{MortgRec}_t$	$\Delta \mathrm{SBLRec}_t$	$\mathrm{ShareRec}_t$	$\mathrm{SpreadRec}_t$	$\Delta \mathrm{MortgRec}_t$	$\Delta \mathrm{SBLRec}_t$	$\mathrm{ShareRec}_t$	$\mathrm{SpreadRec}_t$
$\mathrm{HurrExposure}_t$	5.008***	2.260*	72.15	1,294				
	(7.072)	(1.839)	(1.602)	(1.576)				
$\mathrm{HurrExposure}_{t\text{-}1}$					5.179***	9.395***	90.94**	1,263**
					(4.900)	(4.483)	(2.547)	(2.182)
Observations	19,205	9,408	6,380	1,282	19,205	9,408	5,948	1,229
Adjusted R-squared	0.070	0.117	0.475	0.840	0.147	0.145	0.535	0.865
$\mathrm{Controls}_t$	Yes	Yes	Yes	Yes	No	No	No	No
$\mathrm{Controls}_{t\text{-}1}$	No	No	No	No	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Non-recovery lending

This table reports estimates from the bank-year-level OLS regressions of non-recovery lending on hurricane exposures. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. $\Delta MortgNonRec$ ($\Delta SBLNonRec$) is non-recovery mortgage (small business) lending, which is non-agency mortgages (small business loans) issued to counties that did not experience hurricanes in the current year (for columns 2 and 3) or the previous year (for columns 5 and 6) minus mortgages (small business loans) issued to the same counties a year before the hurricane year, scaled by lagged total loans outstanding. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage (small business loan) data is from the HMDA (CRA) dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) ΔLoan_t	(2) $\Delta \text{MortgNonRec}_t$	(3) $\Delta \text{SBLNonRec}_t$	(4) ΔLoan_t	(5) $\Delta \text{MortgNonRec}_t$	(6) $\Delta \text{SBLNonRec}_t$
HurrExposure_t	8.657	6.442	7.581			
	(0.628)	(1.518)	(0.788)			
$\text{HurrExposure}_{t\text{-}1}$				-5.424	-22.94***	-4.479
				(-0.366)	(-4.256)	(-0.302)
Observations	19,205	19,205	9,408	19,205	19,205	9,408
Adjusted R-squared	0.480	0.058	0.102	0.354	0.139	0.291
Controls_t	Yes	Yes	Yes	No	No	No
$\text{Controls}_{t\text{-}1}$	No	No	No	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Bank-county-year-level analysis

This table reports estimates from the bank-county-year-level OLS regressions of lending and mortgage prices on hurricane exposures. *Mortg* (*SBL*) is non-agency mortgages (small business loans) issued by a bank in a county in a year scaled by lagged total loans of the bank. *Share* is the proportion of mortgages issued by a bank in a county with a positive spread over 3% plus the yield on Treasury securities of comparable maturity. *Spread* is the average spread of mortgages issued by a bank in a county with a positive spread. *HurrExposure* is the bank-county-level exposure to hurricane damage, which is the bank-level *HurrExposure* before summing across all counties in Equation 2. *Controls* include *Size*, *RELoans*, *ConsLoans*, *Tier1Ratio*, *FloatRatio*, and *LoansYield*, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage (small business loan) data is from the HMDA (CRA) dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are two-way clustered by bank and county-year. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Mortg_t	SBL_t	Share_t	Spread_t	Mortg_t	SBL_t	Share_t	Spread_t
HurrExposure_t	1.310***	0.476***	81.22***	1,144***				
	(13.83)	(7.213)	(3.090)	(3.565)				
$\text{HurrExposure}_{t\text{-}1}$					0.502***	0.301***	43.35	770.6***
					(8.819)	(5.009)	(1.621)	(2.676)
Observations	5,046,313	5,042,942	1,243,457	263,462	4,665,335	4,660,210	1,187,654	263,832
Adjusted R-squared	0.537	0.512	0.613	0.780	0.550	0.532	0.616	0.776
Controls_t	Yes	Yes	Yes	Yes	No	No	No	No
$\text{Controls}_{t\text{-}1}$	No	No	No	No	Yes	Yes	Yes	Yes
Bank*County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: The effect of hurricanes on past-due and nonaccrual loans.

This table reports estimates from the OLS regressions of the past due status of loans and nonaccrual loans on hurricane exposures in the previous seven years. $PastDue\_over90$ ($PastDue\_30to89$) is loans that are past due 90 days or more (30 through 89 days) and still accruing scaled by total loans outstanding. $Nonaccrual$ is nonaccrual loans scaled by total loans outstanding. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) PastDue_over90_t	(2) PastDue_30to89_t	(3) Nonaccrual_t
$\text{HurrExposure}_{t-1}$	-0.114	0.221	-3.177***
	(-0.527)	(0.387)	(-3.368)
$\text{HurrExposure}_{t-2}$	-0.297	-0.306	-2.611**
	(-1.452)	(-0.545)	(-2.497)
$\text{HurrExposure}_{t-3}$	0.0462	0.613	1.217
	(0.217)	(1.061)	(1.179)
$\text{HurrExposure}_{t-4}$	-0.336	0.860	1.399
	(-1.584)	(1.487)	(1.300)
$\text{HurrExposure}_{t-5}$	0.0235	1.412**	3.260***
	(0.109)	(2.379)	(2.746)
$\text{HurrExposure}_{t-6}$	0.289	-0.256	2.695**
	(1.307)	(-0.464)	(2.265)
$\text{HurrExposure}_{t-7}$	0.105	-0.0924	0.777
	(0.441)	(-0.147)	(0.642)
Observations	46,158	45,475	46,158
Adjusted R-squared	0.421	0.569	0.631
Controls_t	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes

Table 8: Delayed loss recognition after hurricanes and short-term lending.

This table reports estimates from the bank-year-level OLS regressions of lending and mortgage prices on the interactions of hurricane exposure and expected loss overhang. $\Delta MortgRec/\Delta SBLRec$ ($\Delta MortgNonRec/\Delta SBLNonRec$) is recovery (non-recovery) mortgage/small business lending, as defined in Table 6. $ShareRec$ and $SpreadRec$ are measures of mortgage price, as defined in Table 6. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. OVH is the excess of $ExpLoss$ over ALL, and it measures expected loss overhang. $ExpLoss$ is the estimate of expected lifetime losses scaled by the average loan balance following Lu and Nikolaev (2022). ALL is the reported allowance of loan losses scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current year, and those lagged by one year. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, $LoansYield$, and $ExpLoss$ as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage (small business loan) data is from the HMDA (CRA) dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\Delta MortgRec_t$	(2) $\Delta SBLRec_t$	(3) $ShareRec_t$	(4) $SpreadRec_t$	(5) $\Delta Loan_t$	(6) $\Delta MortgNonRec_t$	(7) $\Delta SBLNonRec_t$
$HurrExposure_t * OVH_t$	321.1**	388.0**	-5,355	170,176*	-2,420	-19.04	-2,261*
	(2.107)	(2.072)	(-0.731)	(1.731)	(-0.850)	(-0.0266)	(-1.767)
$HurrExposure_t$	-42.43**	44.49*	239.8	3,905	-202.9	-217.4***	-102.8
	(-2.539)	(1.829)	(0.320)	(0.466)	(-0.643)	(-2.661)	(-0.603)
OVH_t	-0.0102	0.0224	1.737	-39.23*	4.902***	0.106	0.533**
	(-0.704)	(1.205)	(1.102)	(-1.953)	(8.693)	(1.013)	(2.126)
Observations	8,485	6,976	3,544	833	8,485	8,485	6,976
Adjusted R-squared	0.147	0.148	0.583	0.855	0.477	0.082	0.228
$Controls_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$HurrExposure_t * Controls_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Delayed loss recognition after hurricanes and long-term loan losses.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on the triple interaction between loan growth, expected loss overhand, and cumulative hurricane exposure in the past four quarters for each of the previous seven years. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $\Delta Loan$ is the year-over-year percentage change in total loans outstanding. $Past1YrHurrExp$ is the sum of $HurrExposure$ over the past four quarters. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. OVH is the measure of expected loss overhang, as defined in Table 8. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$ in the current year (as defined in Table 1), as well as $ExpLoss$, $ExpLoss * \Delta Loan$, $ExpLoss * Past1YrHurrExp$, and $Past1YrHurrExp * \Delta Loan * ExpLoss$ in each of the past seven years. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$Past1YrHurrExp_{t-1} * \Delta Loan_{t-1} * OVH_{t-1}$	59.59	211.8	254.4	-166.9
	(0.139)	(0.321)	(0.519)	(-0.486)
$Past1YrHurrExp_{t-2} * \Delta Loan_{t-2} * OVH_{t-2}$	418.7	150.3	633.7	110.0
	(1.125)	(0.236)	(1.429)	(0.495)
$Past1YrHurrExp_{t-3} * \Delta Loan_{t-3} * OVH_{t-3}$	859.8**	-1,617**	1,090**	434.2
	(2.097)	(-2.147)	(2.122)	(1.265)
$Past1YrHurrExp_{t-4} * \Delta Loan_{t-4} * OVH_{t-4}$	-36.96	-883.7	-162.8	-100.00
	(-0.0998)	(-1.374)	(-0.312)	(-0.354)
$Past1YrHurrExp_{t-5} * \Delta Loan_{t-5} * OVH_{t-5}$	362.1	-1,318*	322.4	-15.72
	(1.051)	(-1.784)	(0.661)	(-0.0493)
$Past1YrHurrExp_{t-6} * \Delta Loan_{t-6} * OVH_{t-6}$	453.3	-1,585**	515.9	152.2
	(1.451)	(-2.191)	(1.445)	(0.624)
$Past1YrHurrExp_{t-7} * \Delta Loan_{t-7} * OVH_{t-7}$	611.1**	-852.5	150.5	-391.1*
	(2.046)	(-1.340)	(0.375)	(-1.674)
Observations	14,031	14,031	14,031	14,031
Adjusted R-squared	0.732	0.828	0.698	0.871
Two-way interaction and individual $terms_{t-1 - t-7}$	Yes	Yes	Yes	Yes
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Online Appendix

to

"The impact of climate hazards on banks' long-run performance"

by

Yao Lu and Valeri Nikolaev

Table A1. The effect of SBA loans and FEMA grants on loan losses, profitability, and loan loss recognition after hurricanes.

This table reports estimates from the OLS regressions of loan losses, profitability, and loan loss recognition on the interactions of hurricane exposure and the exposure to SBA loans or FEMA grants in the past seven years. NCO is net charge-offs scaled by the average loan balance. The average loan balance is calculated based on loans outstanding at the end of the current quarter, and those lagged by four quarters. ROA is the sum of pre-tax income and interest expense scaled by the book value of assets. LLP is loan loss provision scaled by the average loan balance. ALL is allowance for loan losses scaled by the average loan balance. $HurrExposure$ is the exposure to hurricane damage, as defined in Equation 2. SBA_FEMA is an indicator variable equal to one if at least one of the hurricane-affected counties that the bank is exposed to received SBA disaster loans or FEMA grants, and zero otherwise. $Controls$ include $Size$, $RELoans$, $ConsLoans$, $Tier1Ratio$, $FloatRatio$, and $LoansYield$, as defined in Table 1. Hurricane damage data is from the SHELDUS dataset. Bank mortgage data is from the HMDA dataset. Bank fundamentals are obtained from FR Y-9C reports available on the website of the Federal Reserve Bank of Chicago. Robust t-statistics are in parentheses. Standard errors are clustered by bank. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) NCO_t	(2) ROA_t	(3) LLP_t	(4) ALL_t
$HurrExposure_{t-1} * FEMA\_SBA_{t-1}$	0.0783	3.684	1.380	1.270
	(0.0469)	(1.270)	(0.760)	(0.814)
$HurrExposure_{t-2} * FEMA\_SBA_{t-2}$	-0.400	2.205	0.272	1.541
	(-0.217)	(0.506)	(0.122)	(0.729)
$HurrExposure_{t-3} * FEMA\_SBA_{t-3}$	1.930	-1.431	0.419	0.275
	(0.760)	(-0.254)	(0.129)	(0.117)
$HurrExposure_{t-4} * FEMA\_SBA_{t-4}$	8.440**	8.178	5.757	-1.081
	(2.269)	(1.208)	(1.254)	(-0.363)
$HurrExposure_{t-5} * FEMA\_SBA_{t-5}$	0.470	-0.0560	-0.441	-0.486
	(0.117)	(-0.00928)	(-0.0920)	(-0.136)
$HurrExposure_{t-6} * FEMA\_SBA_{t-6}$	-5.751	1.281	-7.804*	-3.989
	(-1.373)	(0.232)	(-1.681)	(-1.136)
$HurrExposure_{t-7} * FEMA\_SBA_{t-7}$	-0.433	-1.381	-6.062	-6.705*
	(-0.113)	(-0.290)	(-1.512)	(-1.921)
Observations	46,354	46,354	46,354	46,354
Adjusted R-squared	0.580	0.852	0.577	0.665
$HurrExposure_{t-1\ -\ t-7}$	Yes	Yes	Yes	Yes
$FEMAGrants_{t-1\ -\ t-7}$	Yes	Yes	Yes	Yes
$Controls_t$	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
State*Year-quarter Fixed Effects	Yes	Yes	Yes	Yes