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Climate Risks in the U.S. Banking Sector: Evidence from Operational Losses and Extreme Storms

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Abstract

Using supervisory data from large U.S. bank holding companies (BHCs), we document that BHCs suffer more operational losses during episodes of extreme storms. Among different operational loss types, losses due to external fraud, BHCs' failure to meet obligations to clients and faulty business practices, damage to physical assets, and business disruption drive this relation. Event study estimations corroborate our baseline findings. We further show that BHCs with past exposure to extreme storms reduce operational losses from future exposure to storms. Overall, our findings provide new evidence regarding U.S. banking organizations' exposure to climate risks with implications for risk management practices and supervisory policy.

Keywords: Operational Losses; Banking; Bank Holding Companies; Natural Disasters; Climate Risk; Hurricanes; Tornadoes; Severe Thunderstorms

JEL Classification Codes: G20, G21, G32, Q54

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1. Introduction

Policymakers around the world are earnestly examining the risks that climate change could pose to banking organizations and the financial systems they support.[1] Progressively extreme weather is one possible channel (Board on Natural Disasters, 1999; Intergovernmental Panel on Climate Change, 2012, 2013), whereby the destruction and economic disruptions caused by natural disasters may cascade over to banks and other financial institutions. While prior research recognizes credit losses as a potential channel (e.g., Blickle et al., 2021), much less consideration has been given to operational losses as sources of climate risk to banking organizations.[2] The Basel Committee on Banking Supervision (2021) cautions that there has been only "a very limited focus" to date on the impacts of climate change on operational risk.

This is despite the fact that operational risk is a major source of concern for banking organizations. Curti et al. (2022b) document that operational losses exceeded 25% of net income for the largest U.S. bank holding companies (BHCs) between 2001 and 2016; and Afonso et al. (2019) find that operational risk accounted for 30% of average regulatory capital for these same institutions. Because operational risk is particularly heavy-tailed, it poses unique challenges to BHC capital management and solvency and may even raise financial stability concerns (Berger et al., 2022).

[1] See, for example, *The Wall Street Journal*: "Central Banks Jump Into Climate-Change Policy Fray" (S. Clark, May 16, 2021); "Big Banks Face Climate-Change Tests" (S. Clark, June 8, 2021); "Climate Risks for Big Banks Could Hurt Financial System, OCC Says" (R. Vanderford, Dec. 16, 2021).

[2] Climate change risks can primarily be categorized as physical risks and transition risks (Baudino and Svoronos, 2021). Among these risks, physical risks are those that arise from acute extreme weather events such as storms, and chronic physical risks, which include gradual changes in precipitation, rising sea levels or increasing temperatures. Transition risks are generated by adjustments toward a low carbon economy. They include changes in public policies, in legislation, in regulation, in technology and in customer sentiment.

There are indeed significant risks associated with extreme weather that may translate into higher operational losses. Among other risks, financial institutions' facilities could be damaged or destroyed – e.g., flooded branches and automated teller machines (ATMs). Lack of electrical power or fuel for generators may render computer systems inoperable, and there may be disruptions in communications services, possibly for extended periods of time. Processing transactions, especially electronically, may become extremely difficult or even impossible.[3]

In this study, we size up the disaster channel of operational losses by studying how banking organizations fared against past disasters. In doing so, we focus on extreme storms (hurricanes, tornadoes and severe thunderstorms) for a couple of reasons. First, extreme storms are exogenous shocks that can wreak havoc on bank assets, substantially disrupt bank operations, and cause banks to modify their business practices in ways that give rise to various operational risks. In fact, extreme storms are among the most destructive weather disasters, which have also garnered significant attention in the finance and economics literatures.[4] Second, extreme storms are sufficiently exogenous to a BHC's characteristics and business model, which is crucial for mitigating endogeneity concerns that variations in a BHC's operational losses are due to unobserved BHC heterogeneity or reverse causality (Dessaint and Matray, 2017). Since BHCs affected by an extreme

[3]An example of the consequences of extreme weather is Hurricane Sandy, which battered the U.S. East Coast in late October 2012. The storm caused widespread business disruption and infrastructure damage. In one instance, JPMorgan Chase & Co., Bank of America, Wells Fargo & Co., Citibank and Morgan Stanley closed banking branches and brokerage offices in preparation for Sandy, many of which remained closed after the storm as they either lacked electricity or were inaccessible because of flooding or other damage. See Reuters: "U.S. Banks Report Reopening Local Offices Closed by Storm" (D. Henry and L. T. LaCapra, Oct. 31, 2012). In another instance, Sandy flooded the underground levels, including the vault full of clients' physical securities, of the headquarters of the Depository Trust and Clearing Corporation (DTCC). See Reuters: "DTCC Finds 1.3 Million Soaked Securities in Sandy-flooded NY Vault" (I. Jonas, Nov. 14, 2012).

[4]See, for example, Belasen and Polachek (2008); Yang (2008); Strobl (2011); Dessaint and Matray (2017); Gallagher and Hartley (2017); Deryugina (2017); Schüwer et al. (2018); Rehse et al. (2019); Deryugina and Molitor (2020); Mallucci (2022).

storm are assigned randomly by nature, our setting provides a reasonable foundation for causal inference on the impact of extreme weather on BHCs' operational losses. Although extreme storms may not be completely unexpected events in the regions they impact, the exact timing and path of such storms and the degree of damage they cause cannot be determined in advance (Belasen and Polachek, 2008).[5]

A considerable advantage of our research is the use of detailed supervisory data on operational losses. These data are reported to the Federal Reserve System by large U.S. bank holding companies for stress testing purposes. De Fontnouvelle et al. (2006) and Abdymomunov et al. (2020) caution that public sources of data often omit significant operational loss events. In contrast with the publicly available data commonly used in the operational risk literature, we utilize confidential supervisory data that is significantly richer and more comprehensive. We pair these data with information (e.g., county-level property damage) on hurricanes, tornadoes and severe thunderstorms over 2000:Q1-2019:Q4 from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), see CEMHS (2023). BHC geographical exposure is measured by the proportion of deposits received from branch offices at the county level, information we source from the Federal Deposit Insurance Corporation's Summary of Deposits survey. While combining these data restricts our sample to only 24 large BHCs, these institutions account for the majority of U.S. banking industry assets (76.5% as of 2019:Q4).

[5]We highlight that we do not confound BHC exposure to extreme storms with exposure to other types of natural disasters (e.g., droughts, earthquakes, wildfires, volcanoes). We do so to preserve the homogeneity of potential economic channels at play. The economic channels of BHC losses from extreme storms vis-á-vis other natural disasters can be arguably quite different. For completeness, we study how BHC operational losses are related to natural disasters other than extreme storms in Section 6.3.

Our main findings can be summarized as follows. Using regression models saturated with BHC and quarter fixed effects, we document that banking organizations that operate in counties with higher property damage from hurricanes, tornadoes and severe thunderstorms suffer more operational losses.[6] A plausible 100% increase in our measure of BHC exposure to storms is associated with a 8.4% increase in operational losses. In 2019-constant dollar terms, this translates into a $22 million incremental loss, compared with an average BHC quarterly loss of $262 million. Event study estimations around major destructive storms confirm this core result.

We conduct several exercises aimed at contextualizing the positive relation between BHC operational losses and county-level property damage from storms. First, we investigate the specific types of losses that drive this relation. Consistent with plausible economic channels, we identify those to be losses from External Fraud (EF); Clients, Products, and Business Practices (CPBP); Damage to Physical Assets (DPA); and Business Disruption and System Failures (BDSF). In contrast, we find that losses from Internal Fraud (IF); Employee Practices and Workplace Safety (EPWS); and Execution, Delivery, and Process Management (EDPM) are not significantly related to BHCs' exposure to storms. Second, we document that extreme storm exposure is positively related to the frequency and severity of severe tail operational loss events. Third, we show that the effect of storms on operational losses is driven by major storm events with presidential disaster declarations. Finally, we investigate whether BHC exposure to past major storms mitigates storm effects on future operational losses. We find evidence of such effects, suggesting that banking organizations "learn" to mitigate storm-related threats.

[6]Property damage is aggregated at the BHC level by averaging across all counties where a BHC has branches using deposits as weights.

We extend knowledge in several ways. This study is among the first to provide empirical evidence of climate risks in context of banking. Our findings highlight that severe weather could set off large operational losses at banking organizations. We thus contribute to the emerging climate-finance literature as well as the growing literature on operational risk at financial institutions. In the policy sphere, we add to the ongoing efforts by regulators and researchers to dissect how banks and financial systems will withstand climate change. Our findings suggest the existence of physical climate risks via operational risk channels. Given that most existing frameworks have focused exclusively on credit risk dimensions, our results suggest the need for a more holistic framework to assess bank climate exposures.[7] Our findings also indirectly suggest that climate-related operational losses may degrade banks' ability to provide services to their customers and accommodate increased loan demand after disasters. The sensitivity of specific types of operational losses to severe weather (e.g., losses from external fraud, damage to physical assets or business disruption) may also inform financial institutions' disaster recovery and business continuity plans, complementing formal regulatory guidance (e.g., Federal Financial Institutions Examination Council, 2019).

2. Related Literature

Our study broadly contributes to the emerging climate-finance literature. Gropp et al. (2019) and Bernstein et al. (2019) show that long-run sea level rise is already priced into coastal properties, driven by sophisticated buyers. Baldauf et al. (2020) find salience effects of climate risk pricing. Home prices reflect flood risk more sig-

[7] Academics (e.g., Battiston et al., 2017; Reinders et al., 2020; Vermeulen et al., 2021; Jung et al., 2022), central banks and prudential regulators have often used stress tests to examine banking organizations' exposure to climate risks. However, progress remains slow and focused on credit risk dimensions (Baudino and Svoronos, 2021).

nificantly in neighbourhoods where residents believe in climate change. Krueger et al. (2020) document that climate risks – particularly from regulatory changes – pose significant concerns for institutional investors. Painter (2020) finds that counties more likely to be affected by climate change face higher costs of financing. Vigdor (2008) discusses the impact of Hurricane Katrina on New Orleans and the long-term economic viability of such coastal cities. Strobl (2011) shows that hurricanes depress GDP in affected communities.

A thinner subset of the climate-finance literature specifically focuses on bank stability implications of natural disasters, largely documenting the lack of material adverse effects. Blickle et al. (2021), for example, find that weather disasters had only a small and often insignificant impact on U.S. banks' performance over the last quarter century. Using data from multiple developed countries, Klomp (2014) similarly concludes that natural disasters do not impact bank default risk. A particular explanation is that disasters increase loan demand (Berg and Schrader, 2012; Chavaz, 2016; Cortés and Strahan, 2017; Koetter et al., 2020; Ivanov et al., 2022), which offsets potential losses at banks. By contrast, our study documents significant adverse effects of a specific type of natural disasters – extreme storms – via higher operational losses. These higher losses are related to damage to physical assets, business disruption and system failure, incapacity to meet professional obligations to clients, and increased external fraud committed against the banks. The severe weather events we analyze increase the incidence of high-severity tail operational risk events, which have been shown to undermine financial stability (Berger et al., 2022).

Our study also contributes to the literature on operational risk at financial institutions. Jarrow (2008) describes operational risk with a particular focus on economic capital estimation. Cummins et al. (2006) and Gillet et al. (2010) analyze stock market reactions to operational loss announcements at financial institutions. Cope and Carrivick (2013), Abdymomunov et al. (2020) and Frame et al. (2022) analyze financial industry operational losses over the 2008 crisis period and explicitly link operational risk to the state of the macroeconomy. Chernobai et al. (2012), Wang and Hsu (2013), Abdymomunov and Mihov (2019) and Curti et al. (2022a) show that corporate governance, risk management quality and workforce policies such as employee training are related to operational risk outcomes at financial institutions. Chernobai et al. (2021) show that bank holding company expansions into non-banking activities result in more operational risk. Curti et al. (2022b) and Frame et al. (2020) document that larger and faster-growing banking organizations have higher operational losses per dollar of total assets. While prior research conceptually links climate risks to operational losses at financial institutions (e.g., Grimwade, 2022), this issue has not been studied empirically.[8] Our study thus provides the first empirical evidence how a particular form of climate risk impacts banking organizations through channels other than credit risk – specifically, through higher operational losses.

3. Potential Channels for Elevated Operational Losses

Severe weather may increase operational losses at banking organizations in several ways. Extreme storms may wreak havoc on banks' infrastructure, piling up losses from damage to physical assets. In some cases, bank office facilities can be nearly or completely destroyed. Additionally, damaged vaults and ATMs oftentimes result in currency and valuables being damaged or ruined by water or pollutants.

[8] Grimwade (2022) provides a broad conceptual discussion how changes in human and institutional behaviors, significant and rapid changes in economic metrics and direct physical impacts of climate change might interact to increase operational losses at financial institutions.

In addition, extreme storms can also cripple banks' operations and result in losses from business disruption. Immediate risks include banking organizations' inability to operate offices (e.g., branches) and ATMs for potentially prolonged periods of time.[9] Paper checks stored on bank premises or in ATMs can be destroyed, and banks may have to use alternative means to process those items or suffer related losses.

The effects of extreme storms on electronic payment systems may also be severe. In the aftermath of a storm, the closing of bank offices and the interruption of electrical and telecommunications services may effectively prevent institutions from accepting or sending electronic transactions. These disruptions affect banking organizations' capacity to conduct both customer transactions through electronic funds transfer systems and wholesale funds transfers through Automated Clearing House (ACH) systems. Regulatory requirements may further complicate reinstating operations – e.g., regulators typically require institutions to file applications before moving branch locations or establishing new branches. At the same time, it may take months to recover and rebuild properties damaged by extreme storms.

Extreme storms are expected to increase losses from fraud as professional criminals opportunistically exploit changes in customer behaviors and disruption to firms' processes and controls to perpetrate fraud (Grimwade, 2022). Indeed, the disruption of electronic forms of payments (e.g., debit and credit card payments) may require banks to adapt procedures so they can continue to serve affected communities. For example, customer transactions may have to be conducted on a "stand-in" basis, whereby card-holders can access their accounts immediately

[9] Even where the physical locations are accessible, institutions may face staffing problems due to the displacement of key personnel from their homes.

with verifications made after the fact. Alternatively, institutions may adapt procedures to facilitate cashing checks for non-customers. At the same time, atypical patterns of transactions at bank offices in storm-affected regions make fraudulent transactions more difficult to detect.[10] Adverse disaster impacts on staffing levels or employee abilities may further weaken the effectiveness of controls, increasing the success rates of fraud attempts.

Financial institutions' efforts to resume operations expeditiously after a catastrophic storm may also inadvertently result in workplace safety lapses, increasing losses. (For example, remedies for employees' harmful exposure to contaminated bank records, cash, or contents in safe deposit boxes.) Evacuation orders, safety and health hazards, or damaged infrastructure (e.g., washed-out roads, collapsed bridges, and downed power lines) may also impose costs related to transporting employees either from or into affected areas. Deficient safety protocols in business continuity plans may particularly increase legal risks from failing to protect employees properly.

Operational losses during extreme weather episodes may also increase as a result of legal losses stemming from institutions' inability to provide services to clients. Legal losses may also occur because of the provision of faulty products by banking organizations – e.g., litigation around the transference of market and credit risks to customers and investors without adequately disclosing the sensitivities of those risks to extreme weather. Relatedly, regulators may impose fines on banking organizations as deterrents for mistakes and omissions regarding business practices during natural disasters. For example, banks and their employees may respond inappropriately to an emerging crisis both individually and collec-

[10] Customers and employees remaining in, or evacuating from, affected areas may need unexpectedly large amounts of cash to pay for critical goods and services.

tively – e.g., by failing to treat customers experiencing financial difficulties fairly.[11]

Finally, extreme weather may drive up losses as a consequence of increased market volatility and changes in asset values (e.g., Lanfear et al., 2019). For example, market volatility may occur as a result of disruption to agriculture, damage to physical infrastructure and interruption of supply chains.[12] The increased market volatility from disorderly price adjustments (e.g., fire sales of stranded assets) may, in turn, increase the severity of losses from "fat-fingered" employee mistakes in trading platforms and executions or compound information technology malfunctions.

Altogether, we conclude that extreme storms may translate into multiple types of operational losses, de facto encompassing all Basel II event type categories, which we discuss in the next section of our study.

4. Data Sample and Variable Definitions

4.1. Operational Losses

As noted previously, this study uses supervisory data on operational losses reported by large U.S. BHCs to the Federal Reserve System. The data are collected pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act for stress testing purposes under the Comprehensive Capital Analysis and Review program. The operational loss data we use are submitted according to supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1) form requirements

[11]Regulators may additionally encourage bankers to minimize impediments for customers trying to access their funds, which may include waiving ATM fees and surcharges, increasing daily ATM cash withdrawal limits, easing restrictions on check-cashing for customers and non-customers, and waiving overdraft fees as a result of paycheck interruption, waiving late fees due to late payments caused by interrupted mail service (Federal Deposit Insurance Corporation, 2005).

[12]For example, Hurricane Harvey in August 2017 caused widespread flooding and led to the closure of almost one quarter of the United States' refining capacity. This coincided with average gasoline prices rising by 8%, from $2.33 to $2.52 per gallon (Grimwade, 2022).

and are provided by financial institutions with consolidated assets of $100 billion or more.[13] While the original loss data come from 37 institutions, the availability of branch deposit data requisite for the construction of extreme weather exposure measures described in Section 4.4 reduces the number of institutions in our sample to 24. This small number of institutions nonetheless accounts for the majority of U.S. banking industry assets – 76.5% as of 2019:Q4. The data provide information points such as loss amounts, loss dates, loss classifications, and loss descriptions.

Operational losses are categorized into seven event types consistent with Basel II definitions. They are: Internal Fraud (IF); External Fraud (EF); Employment Practices and Workplace Safety (EPWS); Clients, Products, and Business Practices (CPBP); Damage to Physical Assets (DPA); Business Disruption and System Failures (BDSF); and Execution, Delivery, and Process Management (EDPM). Table 1 presents definitions of the loss event types, while Figure 1 displays the share of total losses and U.S. dollar loss amounts by event type category.

The two most significant event types are Clients, Products, and Business Practices and Execution, Delivery, and Process Management. CPBP accounts for $267 billion of total losses, and EDPM accounts for $56 billion. On the other side of the spectrum, Damage to Physical Assets and Business Disruption and System Failures are the smallest event types. They account for $2 and $4 billion of losses, respectively.

The thresholds for collecting individual operational losses differ across BHCs subject to DFAST. To mitigate the impact of heterogeneous collection thresholds on our results, we follow prior research (e.g., Abdymomunov et al., 2020) to dis-

[13]More information about FR Y-14Q reporting requirements, instructions and forms can be found at: `http://www.federalreserve.gov/apps/reportforms/`.

card operational losses below $20,000, the highest threshold across reporting institutions. The final sample contains 426,393 individual loss events from a total of 24 large BHCs over the period [2000:Q1-2019:Q4].[14] Our data are considerably richer than commercially available data. For instance, Chernobai et al. (2012) analyze a sample of 2,426 loss events from Algo FIRST, and Hess (2011) analyzes around 7,300 loss events from SAS OpRisk Global Data. As discussed in De Fontnouvelle et al. (2006), operational loss data sets based on public information are likely to omit substantial losses, which are otherwise included in the supervisory data that we use.

To examine the relation between operational losses and BHC exposure to severe weather, we aggregate loss data at the BHC-quarter level. We use the quarter when an operational loss event occurred or began for the purpose of aggregation. Specifically, we build an unbalanced panel of 1,380 BHC-quarter observations over the period [2000:Q1-2019:Q4] in keeping with individual BHC data availability.

4.2. Operational Loss Measures

Our main measure of operational losses, *OpLoss*, is the inflation-adjusted total dollar value of operational losses incurred by a BHC during a calendar quarter. Table 2, Panel A shows that the average quarterly BHC loss in our sample is close to $262 million, with a standard deviation of $1,685 million. The high standard deviation relative to the average quarterly operational loss suggests the substantial cross-sectional and time-series variation of losses and also indicates

[14]Per FR Y-14Q instructions, BHCs must report a complete operational losses history "starting from the point-in-time at which the institution began capturing operational loss event data in a systematic manner." Most BHCs in our sample report losses for periods preceding the Dodd-Frank Act. BHCs collected such loss data pursuant to regulatory frameworks such as Basel and for internal use. These data undergo robust quality checks, including regular data exams by Federal Reserve staff and BHC internal audit functions.

that quarterly operational losses are significantly positively skewed. We follow Abdymomunov et al. (2020) and Berger et al. (2022) to calculate *Ln(OpLoss)*, a natural logarithm transformation of BHC quarterly losses to account for the positive skewness of their empirical distribution. In robustness analysis, we also use measures of asset-scaled and income-scaled operational losses. Specifically, *OpLossToAssets* measures the operational losses that occur at a BHC over a calendar quarter as a proportion of the BHC's lagged total assets (multiplied by 1,000). And, *OpLossToIncome* measures the operational losses that occur at a BHC over a calendar quarter as a proportion of the BHC's lagged gross income (again multiplied by 1,000).

Prior literature has documented that individual operational losses are similarly positively skewed and heavy-tailed (e.g., Chernobai and Rachev, 2006; Jobst, 2007). Indeed, a few severe operational risk events account for a large portion of the total dollar losses in our sample. Thus, while we focus on quarterly operational losses of BHCs, we also examine tail operational risk events.

We use three frequency-based measures of tail losses, which are constructed as follows. We begin with the 426,393 individual losses in our sample and divide the dollar loss amounts by the BHCs' total assets. We calculate the 90^{th}, 95^{th} and 99^{th} percentiles of the resulting empirical distribution and classify all severe loss events above the respective percentiles as "tail losses." We then count the number of tail losses that occur at an institution in a given quarter for each tail threshold definition and label the variables *NTailEvt90*, *NTailEvt95*, and *NTailEvt99*, respectively. Finally, we take a natural log transformation of the number of tail events (*Ln(NTailEvt90)*, *Ln(NTailEvt95)*, and *Ln(NTailEvt99)*). For robustness and to better capture the severity of tail operational losses, we also calculate three additional measures – *Ln(TailOpLoss90)*, *Ln(TailOpLoss95)*, and *Ln(TailOpLoss99)*. They are defined as natural log transformations of tail operational dollar losses that occur at a BHC over a calendar quarter using the same percentile threshold definitions we just described. Table 2, Panel A shows that the average quarterly dollar sum of tail events (using the 99$^{\text{th}}$ percentile tail definition) is $177 million, which represents 68% of the average quarterly loss.

4.3. Storms

We use the public Spatial Hazard Events and Losses Database (SHELDUS) for the United States to measure BHC exposure to severe weather. SHELDUS provides county-level hazard information for the United States, with different natural hazard event types (e.g., thunderstorms, hurricanes, flooding, wildfires, and tornadoes).[15] The database includes the date, location (county and state), property losses, crop losses, injuries, and fatalities from disasters that affected each county. SHELDUS is geocoded to allow for spatial aggregation and for the property damage to be distributed equally across affected counties. Weather events are derived from several existing national data sources such as the National Climatic Data Center's storm data publications. Damage is estimated based on reports from insurers and local weather stations. To our knowledge, SHELDUS is the most comprehensive source of monetary damage from natural disasters in the U.S.

As mentioned before, we choose extreme storms (hurricanes, tornadoes and severe thunderstorms) for several reasons. First, the occurrence of an extreme storm contains no information about the probability of a storm occurring again in the near future. For example, Dessaint and Matray (2017) estimate that the occurrence of a hurricane over the prior two years is not significantly related to the

[15] There are a total of 18 hazard types in SHELDUS: avalanches, coastal, drought, earthquakes, flooding, fog, hail, heat, hurricanes, landslides, lightning, severe thunderstorms, tornadoes, tsunamis, volcanoes, wildfires, wind, and winter weather.

local probability of hurricane landfall. This finding is consistent with the climate literature, which shows that hurricane frequency in the U.S. mainland has been mostly stationary since 1850 (e.g., Elsner and Bossak, 2001; Pielke et al., 2005). Second, storm occurrences are plausibly exogenous to time-varying BHC characteristics that may otherwise drive up operational risk. As a result, variations in operational losses observed at the time of a storm cannot easily be attributed to unobserved BHC heterogeneity or reverse causality. Third, extreme storms can inflict heavy damage on the affected regions. We do not confound the effects of extreme storms on BHC operational losses with those of other types of natural disasters. We do so to preserve the homogeneity of potential economic channels at play. For completeness, we examine the relation of BHC operational losses to other natural disasters in Section 6.3.

We aggregate damage within a county over all storm events occurring during a quarter to estimate total disaster damage by county and quarter. Figure 2, Panel A shows that property damage from storms tends to cluster geographically. Specifically, damage is clustered into populated regions, primarily along the coast, as well as, to a lesser extent, in the center of the country. Panel B shows that hurricanes primarily strike the Southeast region. Panels C and D show that tornadoes and severe thunderstorms strike the Midwest, Southeast and the Pacific Coast.

Overall, there are a total of 3,126 unique counties affected by extreme storms over the sample period and about 2,341 unique counties per year. Hurricanes each affect a large number of counties because of their massive scale, so we have 929 counties affected by them. Severe thunderstorms affect even more counties – 3,091 in total – because of their high frequency, while tornadoes affect 2,552 counties. Disaster severity varies substantially by type. As noted by prior research (e.g., Cortés and Strahan, 2017), most disasters mete out relatively small losses at the median, but all types can mete out significant damage in the tails of the distributions. On average, hurricanes are the most destructive storm type.

In some of our analysis, we study the operational loss effects of particularly severe storms. For that purpose, we utilize the major disaster categorization by SHELDUS for events which were declared presidential disasters. These events are sufficiently destructive to a state that its governor formally requests federal assistance from the president through the Federal Emergency Management Agency (FEMA).[16] The disaster declaration designation is usually accompanied by the release of significant federal assistance to the disaster-stricken area (e.g., Blickle et al., 2021). About 88.5% of the property damage in our sample can be attributed to SHELDUS-classified major disasters.

4.4. Measures of BHC Exposure to Storms

A BHC's exposure to a storm in a given county is measured by the extent of property damage from the storm in the county during a calendar quarter. We adjust the damage for inflation. If property damage is not reported for a county-quarter, we assign \$0 of damage to that observation. We next aggregate damage from all storms to the county-quarter level because there could be multiple storms that impact a county in a quarter. As a final step, we construct an extreme storm exposure measure at the BHC-quarter level. To do so, we average damage from storms in a quarter across all counties using the amount of BHC deposits in each county as weight. Deposit information is sourced from the Summary of Deposits

[16] A presidential disaster declaration is generally initiated when a state government issues a request to FEMA. FEMA sends a team to the disaster area to perform a preliminary damage assessment to determine whether the damage is extensive enough to warrant a major disaster designation and, if so, for what types of assistance a county is eligible for (Roth Tran and Wilson, 2022). The types of assistance include (1) public assistance for infrastructure repair, (2) hazard mitigation grants to lessen the effects of future disaster incidents, and (3) assistance for individuals and households. Major disaster declarations are approved and issued solely at the discretion of the president of the United States.

(SOD) data compiled by Federal Deposit Insurance Corporation (FDIC), which report the amount of branch deposits for FDIC-insured institutions as of June 30 of every year in our sample.[17]

Figure 3 presents a heat map at the county level of average deposits held by the BHCs in our sample. Darker colors indicate higher concentration of deposits. The figure indicates high deposit concentrations along both the East and the West Coasts. In contrast, the BHCs in our sample do not engage in significant deposit taking in the center of the country – large parts of the Midwest, Southwest and the Rocky Mountains have low deposit concentrations.

While we analyze BHC data at the quarterly level, the county-level deposit data from the SOD are available only for the end of June every year. Consequently, the deposits as of the end of June in year t are carried forward and used as weights for the following four quarters (from the third quarter of year t to the second quarter of year $t+1$).

Table 2, Panel B reports the summary statistics for the BHC-level storm exposure measures. *Storms* has a mean of \$0.274 million and a standard deviation of \$0.809 million. This suggests that a county accounting for an average proportion of a BHC's deposits suffers \$274,000 (2019-constant dollars) in property damage from storms per quarter. The standard deviation is high relative to the mean, indicating that the distribution of damage is highly positively skewed, driven by a few disasters that wreak havoc on property in the affected counties. To limit the influence of outliers in our regression analysis, we apply a natural logarithm

[17] We do not find deposit information in the SOD for the following institutions that otherwise report operational loss data: Barclays US, BMO Financial, BNP Paribas USA, Credit Suisse Holdings (USA), DB USA, DWS USA, HSBC North America Holdings, MUFG Americas Holdings, RBC US Group Holdings, Santander Holdings USA, Synchrony Financial, TD Group US Holdings, and UBS Americas Holding. As previously noted, this reduces the number of institutions in our sample from 37 to 24.

transformation to our storm exposure measures. Our results also hold if we do not apply a log transformation to our storm exposure indices.

Figure 4 plots the average quarterly index of BHC exposure to extreme storms over time. The figure suggests that the counties with deposit-taking activities of BHCs in our sample suffered more property damage from extreme storms in the earlier part of the sample. Six quarters with particularly high property damage appear prominent. The specific five storms associated with these observations are Tropical Storm Allison (2001:Q2), Hurricane Charley (2004:Q3), Hurricane Katrina (2004:Q3-Q4), Hurricane Ike (2008:Q3), and Hurricane Harvey (2017:Q3).

4.5. Variable Correlations

Table 3 presents pairwise variable correlations as a first step in quantifying the relation between BHC exposure to extreme storms and operational losses at BHCs.

The main measures of operational losses, *Ln(OpLoss)*, and exposure to storms, *Ln(Storms)*, are positively correlated, suggesting that operational losses at BHCs increase when the counties where BHCs operate suffer damage from storms. The correlation coefficient is 0.55, statistically different from 0 at the 1% level. A positive association between BHC operational losses and extreme weather is also evident when one specifically focuses on tail operational loss measures and BHC exposure to particularly destructive storms (i.e., storms with presidential disaster declarations). *Ln(MajorStorms)* is positively and significantly correlated with each of *Ln(NTailEvt90)*, *Ln(NTailEvt99)*, *Ln(TailOpLoss90)* and *Ln(TailOpLoss99)*. This is not true, however, for BHC exposure to other less destructive storms – *Ln(OtherStorms)* in fact exhibits much weaker correlations with the operational loss measures.

5. Regression Results

5.1. Operational Losses

We next employ a regression approach to more rigorously examine whether BHC exposure to extreme storms is related to higher operational losses. In doing so, we follow previous operational risk studies (e.g., Dahen and Dionne, 2010; Cope et al., 2012; Abdymomunov et al., 2020; Curti et al., 2022b) and use ordinary least squares (OLS). We estimate the following main specification:

$$Ln(OpLoss)_{i,t} = \beta_1 Ln(Storms)_{i,t} + \beta_i + \beta_t + \epsilon_{i,t}, \tag{1}$$

where i indexes BHCs and t indexes time periods (quarters). *Ln(OpLoss)* represents log-transformed operational losses incurred by a BHC in a given quarter. *Ln(Storms)* represents a BHC's exposure to extreme storms. It is measured as log-transformed county-level property damage from hurricanes, tornadoes and severe thunderstorms over a calendar quarter. The property damage is averaged across counties where a BHC has branches using BHC deposits in counties as weights.

We include BHC fixed effects, β_i, which absorb potentially different time-invariant levels of operational losses and exposure to extreme weather at banking organizations. The inclusion of BHC fixed effects ensures that the coefficient of interest, β_1, is informed by the within-BHC variations in operational losses and extreme weather exposure (because of BHCs' different geographic footprints and the occurrence of storms). We additionally include calendar quarter fixed effects, β_t, which absorb period-specific shocks common across all BHCs (e.g., industry-level operational risks and trends in nation-wide extreme weather). Our specifications do not include time-varying BHC-level controls. To the extent that such variables are uncorrelated with the regional storms (i.e., the occurrences of storms are exogenous to BHC characteristics), our specifications should properly estimate the relation between *Ln(OpLoss)* and *Ln(Storms)*.[18] We cluster standard errors at the BHC level. Table 4 presents the estimation results.

The coefficient estimate of *Ln(Storms)* in Column (1) is positive and statistically significant at the 1% level, indicating higher operational losses at U.S. BHCs that operate in areas impacted by storms. A plausible 100% increase in *Storms* (given the heavy-tailed nature of storm damage) is associated with a 8.4% increase in *OpLoss*. In 2019-constant dollar terms, this translates into a $22 million increase in quarterly dollar losses at the BHC level, relative to an average BHC quarterly loss of $262 million. In Columns (2) and (3), we show that our results are robust to a redefinition of main dependent variable *Ln(OpLoss)*. Specifically, we use total assets scaled operational losses, *OpLossToAssets*, in Column (2) and gross income scaled operational losses, *OpLossToIncome*, in Column (3). In both cases, the coefficient of *Ln(Storms)* remains positive and statistically significant at conventional levels.

In Columns (4) and (5), we decompose *Ln(OpLoss)* into loss frequency and severity components, respectively. Specifically, *Ln(OpFreq)* is a natural log transformation of the frequency of operational losses incurred by a BHC over a calendar quarter. *Ln(OpSev)* is a natural log transformation of the average operational loss severity experienced by a BHC over a calendar quarter. Column (4) shows that operational loss frequency is significantly positively related with *Ln(Storms)*.[19] While average loss severity is also positively related with *Ln(Storms)*

[18]We confirm the robustness of our results to including time-varying controls (e.g., bank size, leverage, risk management quality, revenue structure and profitability) in addition to BHC and quarter fixed effects in Section 6.2.

[19]In unreported tests, we confirm the robustness of our results to using alternative regression functional forms for count data (e.g., Poisson).

in Column (5), the relation is statistically insignificant at conventional levels. Even though the incidence of severe losses significantly increases when BHCs are exposed to extreme storms (see Section 5.3), the overall increase in the frequency of operational loss events moderates their average severity.

5.2. *Operational Losses by Event Type*

Operational risk is a mixture of different subcomponent risks. As discussed in Section 4.1, the losses in our sample can be sorted into seven Basel II event type categories: Internal Fraud (IF); External Fraud (EF); Employment Practices and Workplace Safety (EPWS); Clients, Products, and Business Practices (CPBP); Damage to Physical Assets (DPA); Business Disruption and System Failures (BDSF); and Execution, Delivery, and Process Management (EDPM). While we documented a robust relation between the exposure to storms and operational losses at banking organizations in the previous section, we have not yet investigated the analogous relation within individual loss types. Our discussion in Section 3 suggests that BHC operational losses in all event types could increase as a result of extreme storms.

To test the premise (or alternatively, if heterogeneous effects of extreme storms exist across operational loss event types), we re-estimate Eq. (1) for each event type separately. The results, presented in Table 5, show that four out of the seven loss categories – in Columns (2), (4), (5) and (6) – are positively and significantly related to BHC exposure to storms. Specifically, exposure to storms increases BHC losses from fraud committed by outsiders (EF), failures to meet obligations to clients and improper business practices (CPBP), damage to banks' physical assets (DPA), and business disruption (BDSF). Notably, losses from DPA have a particularly strong association with BHCs' exposure to extreme weather – the magnitude of the coefficient on *Ln(Storms)* in Column (5) is the largest among the seven specifications.

On the other hand, Columns (1), (3) and (7) show *Ln(Storms)* coefficients that are indistinguishable from zero. Exposure to extreme weather does not appear to significantly impact BHC losses from fraud committed by insiders, employment practices, work place safety, failed transaction processing and relations with counter-parties. Such results suggest that losses in only some operational risk event types are sensitive to BHC exposure to extreme weather.

5.3. Tail Operational Losses

Our analysis in the previous sections investigated the association between exposure to storms and operational losses at banking organizations by modeling the conditional average operational loss. This section, on the other hand, focuses on tail losses. The distinction between experiencing a higher level of operational losses vis-á-vis tail operational loss events is important. A higher-than-average level of operational losses due to extreme weather may have adverse implications for a BHC's performance. However, it does not necessarily pose fundamental concerns for the institution's liquidity and solvency, and consequently the risk of failure, if it's easy to anticipate. In contrast, a higher incidence of tail operational loss events is more concerning, as tail losses may pose difficulties for loss reserving practices and capital management.

As discussed in Section 4.2, we use the log-transformed frequency of tail operational loss events incurred by a BHC over given quarter, *Ln(NTailEvt)*, as a measure of tail risk. For robustness, we use three different tail threshold definitions – the 90^{th}, 95^{th} and 99^{th} percentiles. The pairwise correlations in Table 3 provide some evidence that BHC exposure to storms is associated with higher incidence of tail events. We next show in Table 6 that these associations also persist in a regressions setting similar to Eq. (1).

Specifically, Columns (1)-(3) show that in quarters when BHCs are exposed to storms, they suffer more tail operational loss events. Depending on the tail threshold used, a plausible 100% increase in *Storms* results in 3.3-3.8% increase in the quarterly frequency of tail operational losses. The coefficients of *Ln(Storms)* are significant at the 5% level in each case. Columns (4)-(6) further indicate the robustness of our results to using measures that better capture tail loss dollar amounts rather than tail event frequencies. In each case, *Ln(Storms)* retains its positive coefficient and statistical significance at conventional levels. Overall, we conclude that banking organizations' exposure to extreme storms is relevant not only for average level of operational losses at these institutions but also for the occurrence of improbable, severe tail operational risk events with potential financial stability implications.

5.4. Major Storms Declared Presidential Disasters

Prior research highlights that the bulk of economic losses associated with natural disasters come from relatively few events (Cortés and Strahan, 2017). For example, hurricanes in the 90$^{\text{th}}$ percentile are 500 times more destructive than hurricanes in the 10$^{\text{th}}$ percentile (Blickle et al., 2021). Our models account for this variation by constructing storm exposure measures that vary with the size of the property damage shock to counties where BHCs operate. That said, catastrophic (i.e., particularly severe and destructive) storms might have a nonlinear effect on operational losses relative to other storms. Among other reasons, financial institutions may have infrastructure and procedural defenses, to deal with lower-impact storms. Storms with intensity beyond a certain threshold, however, may overwhelm the banks' existing defenses thereby unleashing significant operational losses at these institutions. Following such intuition, this section examines the operational loss impact of catastrophic storms vis-á-vis lower-impact storms.

We start by decomposing *Ln(Storms)* into two variables: *Ln(MajorStorms)* and *Ln(OtherStorms)*. The first one accounts for property damage from SHELDUS-classified "major storms" for which presidential disaster declarations have been issued. (See Section 4.3 for details on the classification.) The latter one accounts for property damage from all remaining storms. *Ln(MajorStorms)* and *Ln(OtherStorms)* are otherwise constructed analogously to *Ln(Storms)*. We then proceed to test the relation of these two variables with operational loss measures. The results are presented in Table 7.

Panel A, Columns (1) and (2) show that *Ln(MajorStorms)* and *Ln(OtherStorms)* are both individually positively related to our main loss measure *Ln(OpLoss)*. While the coefficient of *Ln(MajorStorms)* is statistically significant, *Ln(OtherStorms)* is imprecisely estimated. In terms of magnitude, the coefficient of *Ln(MajorStorms)* is almost two and a half times larger than that of *Ln(OtherStorms)*. This finding suggests that major destructive storms trigger more operational losses at BHCs than lower-impact ones, with potential non-linear loss effects of storm intensity.

Table 7, Panel B shows that these results largely persist if we use tail operational loss measures instead of *Ln(OpLoss)*. In five out of six specifications, the coefficients of *Ln(MajorStorms)* are positive and significant at least at the 5% level. In one specification, the coefficient is positive, but insignificant at conventional levels (with a p-value of 0.16). In contrast, the coefficients of *Ln(OtherStorms)* are economically smaller and always insignificantly related to tail operational losses.

5.5. Do BHCs Learn from Past Exposure to Major Storms?

The impact of major disasters on banking organizations may prod these firms to respond by enhancing their corrective and resilience controls. For example, financial institutions may implement new (or redevelop existing) business continuity and disaster recovery plans to mitigate the impact of future disasters. Anecdotal evidence suggests that indeed some banking organizations learn from prior exposures to extreme storms.[20] Prior research shows in a similar vein that banks use their presence in a region and local knowledge to mitigate credit risk induced by natural disasters (Blickle et al., 2021).

In this section, we examine whether past exposures to extreme storms help BHCs reduce operational losses from future storms. For this purpose, we decompose *Ln(Storms)* into two separate measures that account for whether counties in which a BHC takes deposits have been previously hit by major storms. Specifically, *Ln(StormsInPrevHitCty)* captures exposure to extreme storms during quarter t in counties that have been previously hit by a major storm (with a presidential disaster designation). *Ln(StormsInNotPrevHitCty)*, in contrast, captures exposure to extreme storms during quarter t in counties that have not been previously hit by a major destructive storm (with a disaster designation). For robustness, we use two different "look-back" horizons of 3 and 5 years, respectively. Apart from sorting counties according whether they have been previously hit by major storms, *Ln(StormsInPrevHitCty)* and *Ln(StormsInNotPrevHitCty)* are defined analogously to *Ln(Storms)*. We then estimate models similar to Eq. (1) but substitute *Ln(Storms)* with its two component measures. Table 8 reports the results.

We find a similar pattern across the six specifications. Regardless of the look-back horizon used, the coefficients of *Ln(StormsInNotPrevHitCty)* are positive and significant at least at the 5% level. In contrast, the coefficients of *Ln(StormsInPrevHitCty)*, while positive, are indistinguishable from zero. These results suggest that the positive nexus between operational losses and exposure to extreme storms is driven mostly by BHCs' operations in counties that have not been impacted by major de-

[20] See, for example, *American Banker*: "'Unfortunately, we've gotten pretty good at this': Popular's CEO in wake of Hurricane Fiona" (O. McCaffrey, Sep. 23, 2022).

structive storms in the past. In contrast, storms in locations with prior exposure to major destructive storms have only muted impact on BHC operational losses. A particular explanation for these results could be that financial institutions learn from past exposure to destructive storms and address storm-related threats. Importantly, however, this effect is localized and does not spill over to operations in locations that have not been impacted by past destructive storms.

6. Additional Analyses

6.1. Event Study Estimations

Section 5.4 shows that major destructive storms are a particularly important driver of higher storm-related operational losses at banking organizations. Moreover, they are events with well-defined starting dates that can plausibly be treated as exogenous extreme weather shocks that are otherwise orthogonal to BHC operational risk. In this section, we use a list of major storms in a event study setting to more precisely identify their effect on BHC operational losses. Such tests, which use short event windows and rigorous fixed effect schemes (discussed below), should eliminate any remaining identification concerns that our results so far do not reflect the relation between extreme storms and operational losses at banking organizations, but rather omitted variables. For example, they specifically impede unlikely interpretations whereby BHCs with high risk appetites both expose themselves to extreme weather risks and also engage in other operationally risky strategies that ultimately drive up operational losses.

We start this analysis by refining the list of SHELDUS-classified major storms used in Section 5.4. Specifically, we additionally require that a storm causes at least $10 million in average property damage per county and that no other storm, similar in severity or more severe, occurs within 30 days of the focal storm's beginning date. Our final sample comprises 26 storm events with an average severity of $134 million in total property damage that impact 18 BHCs over the sample period.

We then employ such data in event study specifications to test whether BHCs that have been affected by extreme storms suffer increased operational losses over a 30-day period after the storm begins relative to a 30-day period before. The specifications regress BHC operational losses, *Ln(OpLoss)*, on an indicator, *Post*, equal to 1 in the (30-day) period after a storm begins, and 0 in the (30-day) period before a storm begins. We use two fixed effect schemes, which include either BHC fixed effects and storm event fixed effects, or alternatively, BHC$\times$storm fixed effects. Standard errors are clustered at the BHC level as before. Table 9 presents the results.

Post is positive and significant at conventional levels across both specifications, suggesting that operational losses increase in the 30 days following the beginning of a major destructive storm that impacts counties with BHC branch operations. It is worth emphasizing that we use the occurrence date (rather than discovery or reporting dates) of operational losses in our analysis, and thus these results do not capture pre-storm operational losses that were only discovered by the BHCs after a storm begins. In Figure 5, we plot the daily average operational dollar losses during the [-90, 90] days around the storms. Consistent with the regression results, one can observe higher BHC operational losses in the wake of major storms.

6.2. Time-varying BHC-level Controls

Our baseline specifications estimated with Eq. (1) include BHC and quarter fixed effects. They do not include time-varying BHC-level controls under the premise that such variables are uncorrelated with the occurrence of extreme storms, and their omission should not thus introduce significant bias in our estimations. In this section, we show that our results are robust to including BHC-level time-varying controls.

Balancing model parsimony with the extensiveness of controls, we focus on five fundamental banking organization characteristics: size, leverage, risk management quality, revenue structure, and profitability. We control for BHC size with a natural log transformation of a BHC's total assets (*Ln(Assets)*). To control for leverage, we include the ratio of total assets to book value of equity (*Leverage*). To control for risk management quality, we use a rating by the Federal Reserve System that assesses the ability of the BHCs' boards of directors and senior management to identify, measure, monitor, and control risk. These ratings range from 1 to 5, with a rating of 1 being the strongest (good) and a rating of 5 being the weakest (bad).[21] To account for revenue structure, we include the ratio of non-interest to interest income (*NII-to-II*). Finally, we include BHC return on equity (*RoE*), measured as the ratio of net income to the book value of equity, which is a common measure of profitability. All control variables are lagged one period relative to operational losses. We then re-estimate Eq. (1) including such time-varying BHC-level controls. Table 10 presents the results.

Columns (1)-(6) show that *Ln(Storms)* retains its positive sign, and its coefficients are stable and statistically significant at the 1% level even after including time-varying BHC-level controls. Consistent with our main results in Table 4, BHC exposure to extreme weather is associated with elevated operational losses.

[21]A detailed description of the BHC Rating System can be found at: https://www.federalregister. gov/documents/2004/12/06/04-26723/bank-holding-company-rating-system.

6.3. Types of Natural Disasters

This study focuses on the effects of extreme storms on BHC operational losses. So far, we have combined three types of storms (i.e., hurricanes, tornadoes and severe thunderstorms) into a single measure of exposure to storms, *Ln(Storms)*. We start this section by decomposing *Ln(Storms)* into measures that capture exposures to hurricanes (*Ln(Hurricanes)*), tornadoes (*Ln(Tornadoes)*) and severe thunderstorms (*Ln(SevereThunderstorms)*) individually. All three measures are constructed analogously to *Ln(Storms)* but are based only on property damage from the respective types of storms.

Table 11, Panel A presents the results. While exposures to any of the three storm types are positively related to operational losses, the effect is statistically and economically strongest for *Ln(Hurricanes)*. The coefficients of *Ln(Tornadoes)* and *Ln(SevereThunderstorms)*, while positive, are not statistically significant at conventional levels. These results thus suggest the particularly important role of hurricanes in the operational loss channel of climate risks.

In addition to storms, SHELDUS also contains information on other types of natural disasters. As previously discussed, several reasons motivate us to focus on storms as opposed to other natural disasters. For completeness, however, this section also examines the potential relations between exposure to various types of natural disasters and operational losses at banking organizations. Table 11, Panel B presents the results.

Each natural disaster exposure measure in the panel is analogous to *Ln(OpLoss)* and constitutes a natural log transformation of property damage from the respective type of natural disaster (e.g., hurricanes, tornadoes, severe thunderstorms, flooding, landslides, hail, wildfires, wind, earthquakes, winter weather, lightnings) over a given calendar quarter. The different natural disasters are ordered according to the magnitude of property damage they cause. *OtherDisasters* refers to a category combining property damage from avalanches, coastal, droughts, fog, heat, tsunamis, and volcanoes (the natural disasters with the least property damage). The results indicate that no measure of exposure to natural disasters in Panel B is significantly related to operational losses at BHCs. These results again highlight the important role of storms, and hurricanes in particular, in BHCs' exposure to climate risk.

7. Conclusion

It is unclear whether and how climate change will impact the financial industry. Extreme weather is one potential channel. Focusing mostly on credit risk aspects, prior research concludes that natural disasters are not a material threat. In contrast, our findings suggest otherwise – climate risks from extreme storms are a significant source of operational losses at banking organizations. Exposure to extreme storms increases BHC losses from fraud committed by outsiders, failures to meet obligations to clients and improper business practices, damage to BHCs' physical assets, and business disruption. We show that storms not only increase the frequency of operational loss events on average, but they tend to increase the incidence of severe tail losses that have been associated with financial stability concerns. Major storms have a disproportionate, non-linear positive impact on operational losses. Last, we find evidence that banking organizations "learn" from exposure to past disasters to mitigate future operational losses. These findings have important implications for risk management and supervisory policy.

While financial institutions cannot prevent or anticipate all disasters, they can prepare and practice for them. Infrastructure resilience and business continuity plans could better position financial institutions to meet challenges from severe weather. Identifying potential threats, assessing their potential impact, assigning priorities, and developing planned responses have been highlighted as basic principles of sound business continuity planning (Federal Financial Institutions Examination Council, 2019).

For policymakers, the climate change regulatory exercises (e.g., climate-scenario analysis and stress testing) that have been developed by various jurisdictions are focused mostly on credit risk and are designed to raise awareness within firms of their exposures to the physical and transition credit risks of climate change (Baudino and Svoronos, 2021). Our findings suggest that operational losses due to climate change may be another dimension of financial institution vulnerability that should be integrated into regulatory frameworks.

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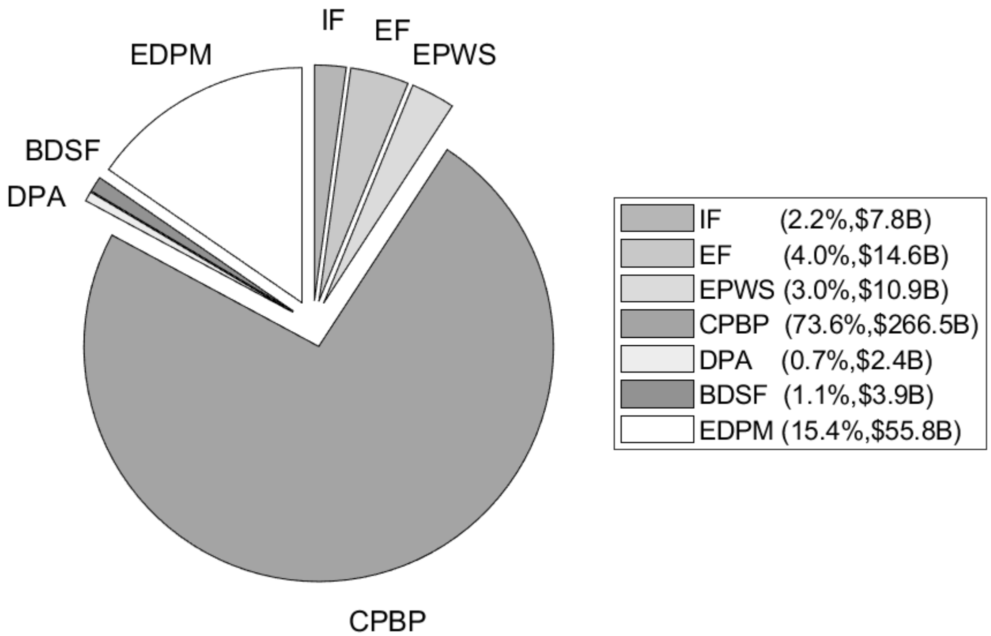
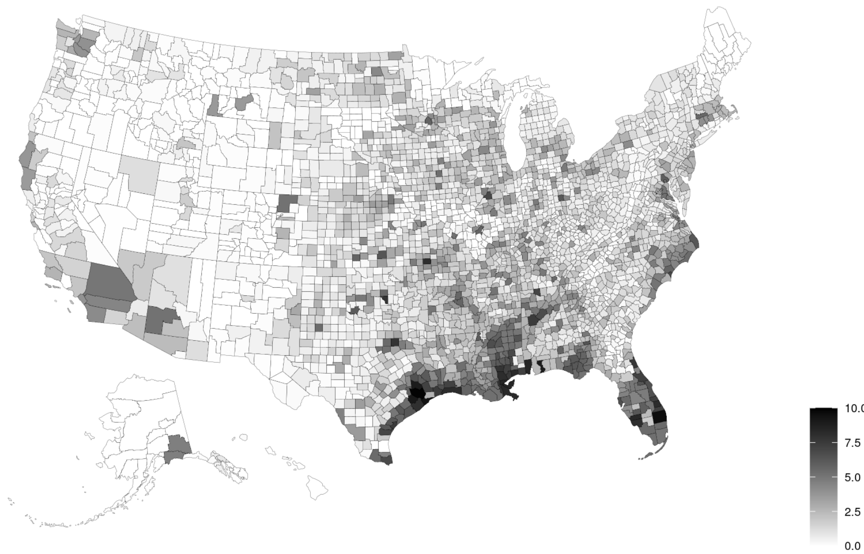


Figure 1: **Operational Losses by Event Type**
This figure presents the allocation of operational loss amounts (percentage of total losses and U.S. dollar loss amounts in billions) by event type. The sample includes 426,393 operational loss events incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). The nomenclature for event types is as follows: Internal Fraud (IF); External Fraud (EF); Employment Practices and Workplace Safety (EPWS); Clients, Products, and Business Practices (CPBP), Damage to Physical Assets (DPA); Business Disruption and System Failures (BDSF); and Execution, Delivery, and Process Management (EDPM). Event type definitions are provided in Table 1, Panel A.

Panel A: All Storms



Panel B: Hurricanes

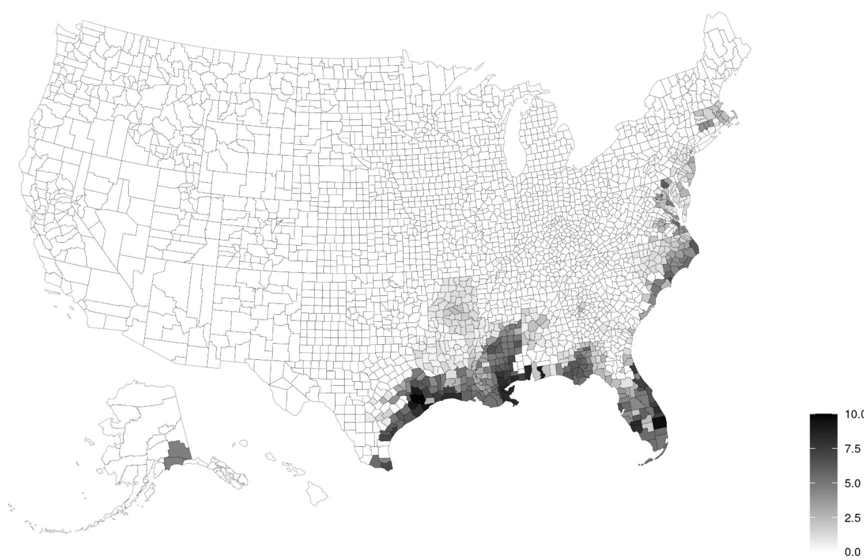
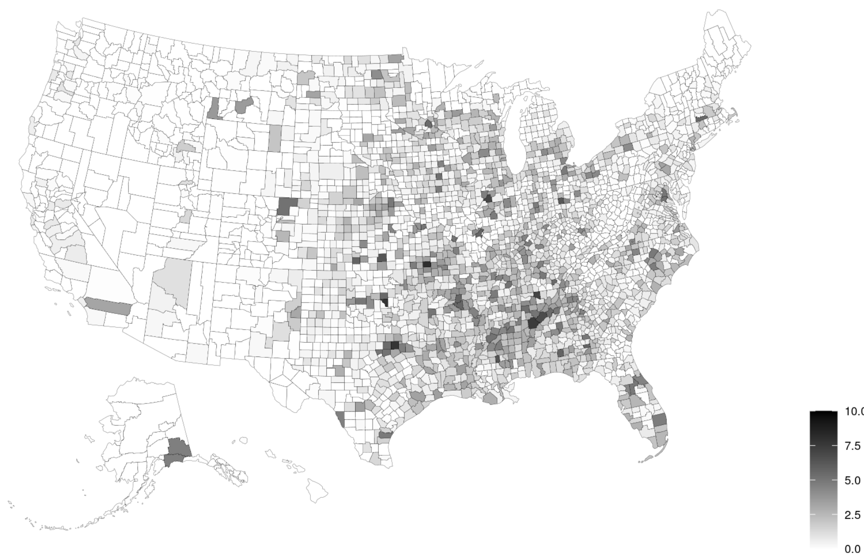
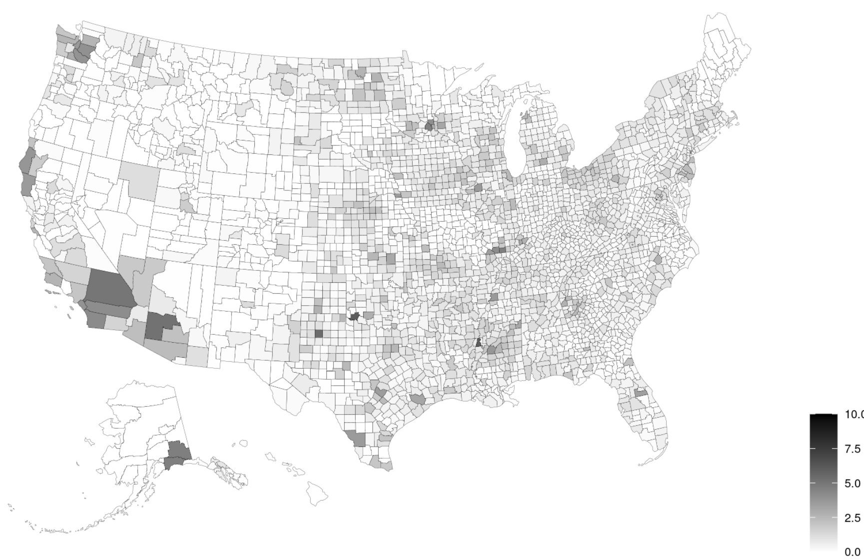


Figure 2: **Geography of Storms Property Damage**
This figure presents a heat map of log-transformed cumulative property damage (U.S. dollars in millions) from storms that occurred in counties across the U.S. over the period [2000:Q1-2019:Q4] based on the Spatial Hazard Events and Losses Database (SHELDUS) data. Darker colors indicate higher property damage. Panel A shows combined property damage from all storm types (hurricanes, tornadoes and severe thunderstorms). Panels B through D show property damage from hurricanes, tornadoes, and severe thunderstorms, separately.

Panel C: Tornadoes



Panel D: Severe Thunderstorms



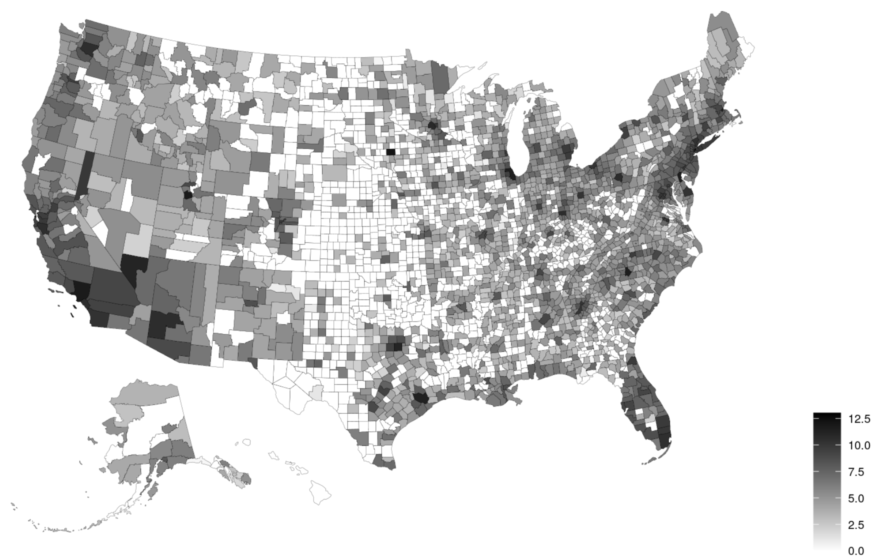


Figure 3: **Geography of BHC Deposits**
This figure presents a heat map of log-transformed average deposits (U.S. dollars in millions) in counties across the U.S. of 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4] based on the FDIC Summary of Deposits data. Darker colors indicate higher deposit concentrations.

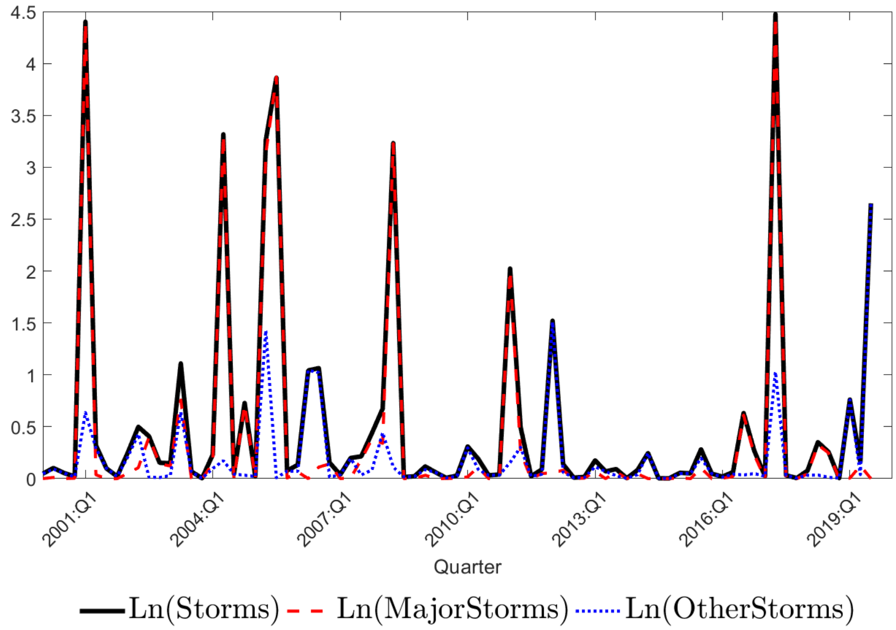


Figure 4: **Storms Exposure of BHCs through Time**
This figure presents plots of extreme storms exposure measures of 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4]. *Storms*, *MajorStorms* and *OtherStorms* measure property damage from storms over a given calendar quarter. This based on combined data from the Spatial Hazard Events and Losses Database (SHELDUS) and FDIC Summary of Deposits. For every BHC, the property damage is averaged across all counties where the BHC has branches using deposits as weights. *Storms* accounts for all storms (i.e., for which presidential disaster declarations were issued or not issued). *MajorStorms* accounts only for storms for which presidential disaster declarations were issued. *OtherStorms* accounts only for storms for which presidential disaster declarations were not issued. The measures are first averaged across BHCs and then log-transformed.

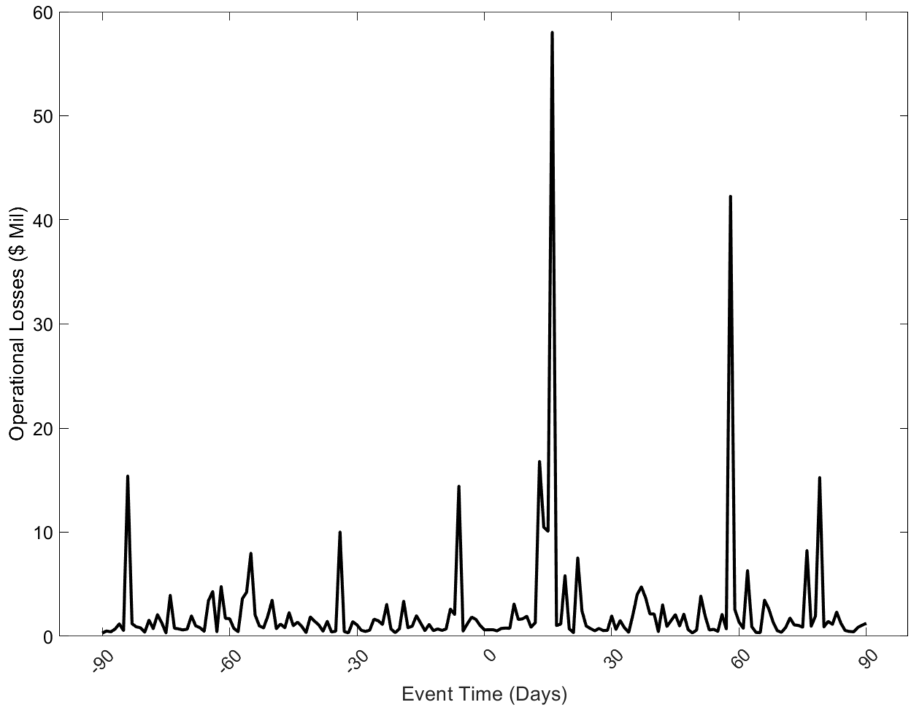


Figure 5: **Operational Losses around Major Storms**
This figure plots the daily average operational dollar losses during the [-90, 90] days around major storms, where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). The sample includes 26 storms that were declared presidential disasters over [2000:Q1-2019:Q4] and caused at least $10 million in average property damage per county based on the Federal Emergency Management Agency (FEMA) data. We require that no other storm (similar or more severe) occurs within 30 days of the storm beginning date. The operational losses are incurred by 18 large U.S. bank holding companies.

Table 1: **Definitions**
This table presents operational loss event type definitions in Panel A and variable definitions in Panel B.

Panel A: Event Types

Event Type Category	Short	Description
Internal Fraud	IF	Acts of a type intended to defraud, misappropriate property or circumvent regulations, which involves at least one internal party.
External Fraud	EF	Acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party.
Employment Practices and Workplace Safety	EPWS	Acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events.
Clients, Products and Business Practices	CPBP	An unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product.
Damage to Physical Assets	DPA	Damage to physical assets from natural disasters or other events.
Business Disruption and System Failures	BDSF	Disruption of business or system failures.
Execution, Delivery and Process Management	EDPM	Failed transaction processing or process management, from relations with trade counterparties and vendors.

Panel B: Variables

Dependent Variables: *Operational Loss Measures*	
OpLoss	Operational losses that occur at a BHC over a calendar quarter in millions of U.S. dollars.
Ln(OpLoss)	A natural log transformation of *OpLoss*, defined as *Ln(1+OpLoss)*.
OpLossToAssets	Operational losses that occur at a BHC over a calendar quarter as a proportion of the BHC's total assets multiplied by 1,000.
OpLossToIncome	Operational losses that occur at a BHC over a calendar quarter as a proportion of the BHC's gross income multiplied by 1,000.
OpFreq	The frequency of operational loss events that occur at a BHC over a calendar quarter in thousands.
Ln(OpFreq)	A natural log transformation of *OpFreq*, defined as *Ln(1+OpFreq)*.
OpSev	The average severity of an operational loss event that occurs at a BHC in a calendar quarter, defined as the ratio of *OpLoss* and *OpSev*.
Ln(OpSev)	A natural log transformation of *OpSev*, defined as *Ln(1+OpSev)*.
NTailEvt	The number of loss events that occur at a BHC over a calendar quarter with a ratio of loss amount to BHC assets higher than the 90th, 95th or 99th percentile of the unconditional distribution of the ratio.
Ln(NTailEvt)	A natural log transformation of *NTailEvt*, defined as *Ln(1+NTailEvt)*.
TailOpLoss	Operational losses that occur at a BHC over a given calendar quarter in millions of U.S. dollars with a ratio of loss amount to BHC assets higher than the 90th, 95th or 99th percentile of the unconditional distribution of the ratio.
Ln(TailOpLoss)	A natural log transformation of *TailOpLoss*, defined as *Ln(1+TailOpLoss)*.
Independent Variables: *Severe Weather and Other Variables*	
Storms	Property damage from storms over a given calendar quarter in millions of U.S. dollars. Property damage is averaged across all counties where a BHC has branches using deposits as weights. *MajorStorms* and *OtherStorms* refer to storms for which presidential disaster declarations were issued and were not issued, respectively. *StormsInPrevHitCty* and *StormsInNotPrevHitCty* refer to storms in counties that have been previously hit or not hit (horizon of 3, 5 or 10 years) by a major storm with a presidential disaster declaration, respectively.
Ln(Storms)	A natural log transformation of *Storms*, defined as *Ln(1+Storms)*.
Assets	BHC total assets (in billions of U.S. dollars).

Panel B (Continued)	
Ln(Assets)	A natural log transformation of *Assets*, defined as *Ln(Assets)*.
Leverage	BHC total assets divided by book value of equity.
RiskManagement	A risk management rating of a BHC assigned by the Federal Reserve System.
NII-to-II	The ratio of BHC non-interest income to interest income.
RoE	BHC return on equity.

Table 2: **Descriptive Statistics**
This table presents descriptive statistics of operational loss measures in Panel A, extreme storms exposure measures in Panel B, and other variables used in our analyses in Panel C. The sample includes 1,380 quarterly observations of 24 large bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). Variables definitions are reported in Table 1, Panel B.

Panel A: Dependent Variables

	N	Mean	Std	P25	P50	P75
OpLoss	1,380	262.244	1,684.761	6.711	23.047	113.947
OpLossToAssets	1,380	0.381	1.311	0.044	0.099	0.252
OpLossToIncome	1,380	12.160	49.475	1.251	2.721	6.975
OpFreq	1,380	310.436	445.856	42.000	118.000	374.500
OpSev	1,380	31.044	3.029	0.112	0.189	0.355
NTailEvt90	1,380	15.522	30.645	13.000	22.000	38.000
NTailEvt95	1,380	3.104	15.227	6.000	11.000	19.500
NTailEvt99	1,380	3.062	3.369	1.000	2.000	4.000
TailOpLoss90	1,380	193.439	1,331.540	4.717	14.675	72.496
TailOpLoss95	1,380	189.069	1,329.605	3.911	12.400	66.286
TailOpLoss99	1,380	176.932	1,324.997	1.029	7.174	49.706

Panel B: Key Independent Variables						
	N	Mean	Std	P25	P50	P75
Storms	1,380	3.886	33.325	0.001	0.021	0.118
Hurricanes	1,380	3.339	33.028	0.000	0.000	0.000
Tornadoes	1,380	0.468	4.588	0.000	0.003	0.030
SevereThunderstorms	1,380	0.079	0.433	0.000	0.007	0.028
MajorStorms	1,380	3.425	32.618	0.000	0.000	0.002
OtherStorms	1,380	0.465	4.047	0.001	0.016	0.072
StormsInPrevHitCty3Y	1,380	19.345	237.304	0.000	0.000	0.000
StormsInNotPrevHitCty3Y	1,380	2.191	26.891	0.000	0.000	0.001
StormsInPrevHitCty5Y	1,380	16.850	218.768	0.000	0.000	0.000
StormsInNotPrevHitCty5Y	1,380	2.129	26.810	0.000	0.000	0.000

Panel C: Other Variables						
	N	Mean	Std	P25	P50	P75
Assets	1,380	519,785	681,773	98,384	173,447	679,651
Leverage	1,380	9.337	2.527	7.512	8.900	10.947
RiskManagement	1,380	2.375	0.517	2.000	2.000	3.000
NII-to-II	1,380	1.044	1.004	0.457	0.630	1.084
RoE	1,380	0.067	0.066	0.034	0.061	0.097

Table 3: **Variable Correlations**

This table presents variable correlations. The sample includes 1,380 quarterly observations of 24 large bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). Variable definitions are reported in Table 1, Panel B. p-values are presented in parentheses.

	Ln (OpLoss)	Ln (NTail Evt90)	Ln (NTail Evt99)	Ln (TailOp Loss90)	Ln (TailOp Loss99)	Ln (Storms)	Ln (Major Storms)	Ln (Other Storms)
Ln(OpLoss)	1.000							
Ln(NTailEvt90)	0.548	1.000						
	(0.000)							
Ln(NTailEvt99)	0.608	0.667	1.000					
	(0.000)	(0.000)						
Ln(TailOpLoss90)	0.993	0.551	0.645	1.000				
	(0.000)	(0.000)	(0.000)					
Ln(TailOpLoss99)	0.921	0.484	0.740	0.950	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
Ln(Storms)	0.074	0.043	0.054	0.070	0.064	1.000		
	(0.006)	(0.107)	(0.043)	(0.010)	(0.018)			
Ln(MajorStorms)	0.078	0.060	0.062	0.074	0.073	0.895	1.000	
	(0.004)	(0.026)	(0.022)	(0.006)	(0.007)	(0.000)		
Ln(OtherStorms)	0.027	-0.013	0.009	0.026	0.015	0.681	0.311	1.000
	(0.309)	(0.638)	(0.739)	(0.337)	(0.568)	(0.000)	(0.000)	

Table 4: **Storms and Operational Losses**
This table reports coefficients from panel regressions of operational losses on extreme storms. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *OpLossToAssets* measures the operational losses that occur at a BHC over a given calendar quarter as a proportion of the BHC's total assets (multiplied by 1,000). *OpLossToIncome* measures the operational losses that occur at a BHC over a given calendar quarter as a proportion of the BHC's gross income (again multiplied by 1,000). *Ln(OpFreq)* is a natural log transformation of the frequency of operational losses incurred by a BHC over a given calendar quarter. *Ln(OpSev)* is a natural log transformation of the average operational loss severity experienced by a BHC over a given calendar quarter. *Ln(Storms)* is a natural log transformation of property damage from storms over a given calendar quarter. The property damage is averaged across all counties where a BHC has branches using deposits as weights. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	(1) Ln (OpLoss)	(2) OpLoss ToAssets	(3) OpLoss ToIncome	(4) Ln (OpFreq)	(5) Ln (OpSev)
Ln(Storms)	0.084***	0.073*	4.079**	0.041**	0.029
	(0.002)	(0.074)	(0.048)	(0.027)	(0.158)
BHC FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.751	0.110	0.122	0.887	0.179

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: **Operational Loss Event Types**

This table reports coefficients from panel regressions of operational losses on extreme storms by loss event type. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. There are 7 operational loss event types: Internal Fraud (IF); External Fraud (EF); Employment Practices and Workplace Safety (EPWS); Clients, Products, and Business Practices (CPBP); Damage to Physical Assets (DPA); Business Disruption and System Failures (BDSF); and Execution, Delivery, and Process Management (EDPM). The dependent variable, *Ln(OpLoss)*, is a natural log transformation of operational dollar losses in a given event type that occur at a BHC over a given calendar quarter. *Ln(Storms)* is a natural log transformation of property damage from storms over a given calendar quarter. Property damage is averaged across all counties where a BHC has branches using deposits as weights. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	Ln(OpLoss)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM
Ln(Storms)	-0.003	0.048^{**}	-0.002	0.069^{*}	0.087^{***}	0.054^{***}	0.023
	(0.901)	(0.017)	(0.948)	(0.068)	(0.009)	(0.002)	(0.365)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.481	0.762	0.791	0.648	0.302	0.751	0.498

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: **Tail Operational Losses**

This table reports coefficients from panel regressions of tail operational losses on extreme storms. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(NTailEvt)* is a frequency-based measure of tail operational losses defined as the natural log transformation of the number of operational loss events that occur at a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 90^{th}, 95^{th} or 99^{th} percentile of the unconditional distribution of the ratio. *Ln(TailOpLoss)* is a dollar-based measure of tail operational losses defined as the natural log transformation of operational losses from events that occur at a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 90^{th}, 95^{th} or 99^{th} percentile of the unconditional distribution of the ratio. *Ln(Storms)* is a natural log transformation of property damage from storms over a given calendar quarter. Property damage is averaged across all counties where a BHC has branches using deposits as weights. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	Ln(NTailEvt)			Ln(TailOpLoss)		
	(1)	(2)	(3)	(4)	(5)	(6)
	90	95	99	90	95	99
Ln(Storms)	0.033^{**}	0.038^{**}	0.034^{**}	0.091^{***}	0.095^{***}	0.097^{**}
	(0.043)	(0.020)	(0.012)	(0.002)	(0.003)	(0.021)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.581	0.551	0.454	0.692	0.670	0.542

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: **Major Storms**

This table reports coefficients from panel regressions of operational losses (Panel A) and tail operational losses (Panel B) on extreme storms. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Ln(NTailEvt)* is a frequency-based measure of tail operational losses defined as the natural log transformation of the number of operational loss events that occur at a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 90^{th}, 95^{th} or 99^{th} percentile of the unconditional distribution of the ratio. *Ln(TailOpLoss)* is a dollar-based measure of tail operational losses defined as the natural log transformation of operational losses from events that occur at a BHC over a calendar quarter that have a ratio of loss amount to BHC assets higher than the 90^{th}, 95^{th} or 99^{th} percentile of the unconditional distribution of the ratio. *Ln(MajorStorms)* is a natural log transformation of property damage over a given calendar quarter from storms for which presidential disaster declarations were issued. *Ln(OtherStorms)* is a natural log transformation of property damage over a given calendar quarter from storms for which presidential disaster declarations were not issued. For both variables, property damage is averaged across all counties where a BHC has branches using deposits as weights. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

Panel A: All Operational Losses

	Ln(OpLoss)		
	(1)	(2)	(3)
Ln(MajorStorms)	0.106***		0.107***
	(0.000)		(0.001)
Ln(OtherStorms)		0.043	−0.006
		(0.457)	(0.912)
BHC FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
N	1,380	1,380	1,380
Adj R^2	0.751	0.750	0.751

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Tail Operational Losses

	Ln(NTailEvt)			Ln(TailOpLoss)		
	(1)	(2)	(3)	(4)	(5)	(6)
	90	95	99	90	95	99
Ln(MajorStorms)	0.066***	0.059***	0.030	0.105***	0.104***	0.122**
	(0.005)	(0.001)	(0.157)	(0.002)	(0.003)	(0.012)
Ln(OtherStorms)	−0.061	−0.024	0.029	0.016	0.030	−0.004
	(0.103)	(0.577)	(0.469)	(0.794)	(0.660)	(0.971)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.582	0.552	0.454	0.692	0.670	0.542

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: **Previous BHC Exposure to Extreme Storms**

This table reports coefficients from panel regressions of operational losses on extreme storms. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Ln(StormsInPrevHitCty)* and *Ln(StormsInNotPrevHitCty)* are natural log transformations of property damage from storms over a given calendar quarter. Property damage is averaged across counties where a BHC has branches using deposits as weights. In the case of *Ln(StormsInPrevHitCty)*, the counties have been previously hit by a major storm with a presidential disaster declaration. In the case of *Ln(StormsInNotPrevHitCty)*, the counties have not been previously hit by a major storm with a presidential disaster declaration. Two different look-back horizons for the occurrence of major storms of 3 and 5 years are used, respectively. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	Ln(OpLoss)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(StormsInPrevHitCty3Y)	0.021		0.002			
	(0.472)		(0.949)			
Ln(StormsInNotPrevHitCty3Y)		0.111***	0.110**			
		(0.008)	(0.036)			
Ln(StormsInPrevHitCty5Y)				0.022		0.005
				(0.418)		(0.886)
Ln(StormsInNotPrevHitCty5Y)					0.121***	0.119**
					(0.003)	(0.016)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.750	0.751	0.751	0.750	0.751	0.751

$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

Table 9: **Event Study Estimations Around Major Storms**
This table reports coefficients from event study estimations of operational losses around major storms. The sample includes 26 storms that were declared presidential disasters over [2000:Q1-2019:Q4] and caused at least $10 million in average property damage per county. We require that no other storm (similar or more severe) occurs within 30 days of the storm beginning date. The operational losses are incurred by 18 large U.S. bank holding companies, where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of the cumulative operational dollar losses incurred by a BHC over the [-30,-1] days prior to a storm or the [0,29] days after a storm begins. *Post* is an indicator variable that equals 1 after a storm begins, and 0 before a storm begins. The specification in Column (1) includes BHC and storm-event fixed effects. The specification in Column (2) includes BHC$\times$storm-event fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	Ln(OpLoss)	
	(1)	(2)
Post	0.281**	0.281*
	(0.020)	(0.088)
BHC FE	Yes	No
Event FE	Yes	No
BHC * Event FE	No	Yes
N	652	652
Adj R^2	0.681	0.829

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 10: **Time-Varying BHC-level Controls**

This table reports coefficients from panel regressions of operational losses on extreme storms. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. *Ln(Storms)* is a natural log transformation of property damage from storms over a given calendar quarter. Property damage is averaged across all counties where a BHC has branches using deposits as weights. *Ln(Assets)* is a natural log transformation of BHC total assets. *Leverage* is BHC total assets divided by book value of equity. *RiskManagement* is the risk management rating of a BHC assigned by the Federal Reserve System (ranging from 1 to 5, with higher values denoting weaker risk management practices). *NII-to-II* is the ratio of BHC non-interest income to interest income. *RoE* is the return on equity of BHC. All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

	Ln(OpLoss)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Storms)	0.077***	0.084***	0.085***	0.084***	0.085***	0.076***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)
Ln(Assets)	0.511					0.536*
	(0.101)					(0.078)
Leverage		−0.001				−0.019
		(0.987)				(0.652)
RiskManagement			−0.137			−0.143
			(0.792)			(0.765)
NII-to-II				−0.111		−0.116
				(0.393)		(0.299)
RoE					−0.214	−0.116
					(0.742)	(0.838)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.754	0.751	0.751	0.751	0.751	0.754

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 11: **Types of Natural Disasters**

This table reports coefficients from panel regressions of operational losses on natural disasters. The estimation sample comprises an unbalanced panel of 1,380 quarterly losses incurred by 24 large U.S. bank holding companies over the period [2000:Q1-2019:Q4], where operational loss data come from the supervisory FR Y-14Q Operational Loss Data Collection Schedule (E.1). *Ln(OpLoss)* is a natural log transformation of operational dollar losses incurred by a BHC over a given calendar quarter. Each natural disaster exposure measure is a natural log transformation of property damage from the respective type of natural disaster (e.g., hurricanes, tornadoes, severe thunderstorms, flooding, landslides, hail, wildfires, wind, earthquakes, winter weather, lightnings) over a given calendar quarter. *OtherDisasters* refers to a category combining property damage from avalanches, coastal, droughts, fog, heat, tsunamis, and volcanoes. Property damage is averaged across all counties where a BHC has branches using deposits as weights. Panel A presents a decomposition of extreme storms into three separate types of storms: hurricanes, tornadoes and severe thunderstorms. Panel B presents measures of natural disasters other than extreme storms (ordered according to the magnitude of property damage). All specifications include BHC and quarter fixed effects. The error terms are clustered at the BHC level. p-values are presented in parentheses.

Panel A: Types of Storms

	Ln(OpLoss)		
	(1)	(2)	(3)
Ln(Hurricanes)	0.113***		
	(0.000)		
Ln(Tornadoes)		0.018	
		(0.705)	
Ln(SevereThunderstorms)			0.106
			(0.478)
BHC FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
N	1,380	1,380	1,380
Adj R^2	0.751	0.750	0.750

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Other Natural Disasters

	Ln(OpLoss)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Flooding)	0.009								
	(0.816)								
Ln(Landslides)		−0.012							
		(0.908)							
Ln(Hail)			0.033						
			(0.604)						
Ln(Wildfires)				−0.039					
				(0.686)					
Ln(Wind)					−0.035				
					(0.779)				
Ln(Earthquakes)						0.006			
						(0.982)			
Ln(WinterWeather)							−0.057		
							(0.527)		
Ln(Lightnings)								0.094	
								(0.701)	
Ln(OtherDisasters)									−0.159
									(0.485)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380	1,380
Adj R^2	0.750	0.750	0.750	0.750	0.750	0.750	0.750	0.750	0.750

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$