Is Flood Risk Priced in Bank Returns?

Valentin Schubert*

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Abstract

Policymakers are concerned about the effect of climate change on financial stability. However, estimating the exposure of financial institutions to climate risks is inherently difficult. In this paper, I first quantify the costs of realized flood disasters for banks. Second, I create a novel bank-level flood risk exposure measure for U.S. banks using expected flood risk estimates and mortgage lending data. Following flood disasters, the profitability and capital ratios of affected banks decrease. The effect holds across different bank subsamples and is persistent over time. Yet, in the cross-section of returns, stocks of small banks with high exposure to flood risk underperform. Removing disaster months or controlling for past disaster shocks cannot explain this flood risk discount. The underperformance persists even when adjusting for investors' climate change concerns. The results suggest that climate change negatively affects banks and that markets are underreacting to such risks, especially when pricing smaller banks. Therefore, policymakers' concerns may be warranted for smaller institutions.

Keywords: Banks, Stock returns, Climate change
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1. Introduction

In the United States, weather disasters have caused over $1 trillion in property damages since 2010.[1] Worldwide climate change is likely affecting the intensity and frequency of hazards (National Academies of Sciences, 2016). The widespread consensus is that without drastic measures, costs from climate change-related disasters will increase further over the next decades (Intergovernmental Panel on Climate Change, 2015). Some estimates warn that property damages from floods will likely increase by more than 60% over the next 30 years (First Street Foundation, 2021). Policymakers are increasingly worried that disruptions caused by natural disasters could negatively affect financial stability. In particular, regulators are concerned that markets neglect the physical risks from climate change and underreact to the exposure (e.g., Carney, 2015; Lagarde, 2021). Despite regulators' policy actions in conducting climate-related stress tests in several countries, there is limited empirical evidence of how physical risks from climate change affect the financial system.[2]

In this paper, I first evaluate the costs of flood disasters on bank performance. Banks exposed to realized floods have a lower return on assets and a lower Tier 1 capital ratio. The estimates are quantitatively similar for large and small banks, which suggests that even larger banks do not fully hedge the costs associated with flooding. In addition, banks with a larger share of mortgages to their total assets exhibit higher non-performing loan and loan charge-off ratios. Second, I introduce a novel bank-level measure of flood risk for banks in the United States and assess whether the risks from flooding are priced in the cross-section of US bank stocks. I find that banks with high exposure to the risk of flooding underperform compared to non-exposed banks. This result implies a risk exposure *discount*. The effect is sizeable. A one-standard-deviation increase in flood risk exposure is linked to a 2.4 percentage points (pp) lower annualized return. The flood risk exposure is a robust return predictor and cannot be explained by other bank characteristics in cross-sectional regression using pooled OLS. Further, a portfolio of banks with high exposure to flood risk underperforms a portfolio of non-exposed banks on average by 5% per year. A selection of standard factors does not subsume the negative alpha.

To measure the costs of floods for banks, I combine flood damage estimates from Sheldus with mortgage-level data. The measure builds on the notion that banks are exposed to floods through their mortgage portfolio and associated collaterals. The measure of flood damage exposure is constructed in two steps. First, I depart from the existing

[1]From 1980, costs from billion-dollar natural disasters amount to $2.3 trillion, with a significant increase in inflation-adjusted costs in the last five to ten years. See `https://www.ncei.noaa.gov/access/billions/` for more details, accessed in August 2022.

[2]The Bank of England published first climate-related scenario analysis in June 2021, followed by the European Central Bank (ECB) shortly after. More recently financial regulators in Canada and France incorporated climate change analyses in their assessments (Brainard, 2021).

literature and define the bank-level regional weights as the share of retained mortgage amount by a bank in a county relative to its total retained mortgage amount in a given year using mortgage-level location information. As the mortgage portfolio exposes banks to costs from floods, measuring the exposure from banks' assets rather than branch-level information allows me to capture the exposure more closely.[3] Second, the regional weights are matched to the estimated flood damages to calculate a bank-level aggregate flood damage exposure.

Flood disasters significantly decrease bank profitability and increase leverage ratios. The effect on return on assets persists for up to one year. The point estimates show that a one-billion-dollar flood is associated with a 4% lower return on assets.[4] Even after one year, equity ratios are still below their pre-disaster levels and show no sign of reverting back. Furthermore, the outcomes of small and large banks are equally affected. For banks specializing in mortgage lending, non-performing loans and mortgage charge-offs are significantly higher for several quarters after major flood disasters. As non-performing loans are measured with a lag, the full effect is only measured two and three quarters after the flood disaster. Further, I illustrate the negative relation between natural disasters and bank equity with Hurricane Katrina. Within a few days, after the hurricane made landfall, banks only lending to affected counties had abnormal returns of -15% compared to banks lending in other counties of the U.S. Gulf Coast region and neighboring states. The finding suggests that markets recognize the risks from natural disasters to banks at least as the risks materialize. The next question is whether investors demand ex-ante compensation for the additional risks.

To measure flood risks for banks, I combine expected flood risk estimates from First Street Foundation (FSF) with the bank-level regional weights.[5] I examine the cross-sectional relation between flood risk exposure and US bank stock returns by running bank-level Fama and MacBeth (1973) and pooled OLS regressions. Bank-level excess return and flood risk exposure have a strong negative relation, which suggests a return discount for exposure to the risk of flooding. A one standard deviation increase in the flood risk exposure is linked to a 2.4 percentage point lower annualized excess return. The finding is in line with physical risk from climate not being adequately priced as previously documented for non-bank equities.[6] Interestingly, banks' stock return underperformance

[3]For example, Blickle, Hamerling, and Morgan (2021) use branch information and find no clear effect on profitability.

[4]In the last five years, the U.S. experienced around 18 billion-dollar disasters (NOAA, 2022).

[5]The data is created by researchers at George Mason University, Fathom Global, and the Rhodium Group, which specialize in modeling flood risk and producing climate change-related data.

[6]Hong, Li, and Xu (2019) show that physical risk from drought is not priced in food-producing industries, while Faccini, Matin, and Skiadopoulos (2021); Acharya, Johnson, Sundaresan, and Tomunen (2022) find that rising temperatures and storms, respectively, are not priced in U.S. stocks.

varies with banks' size or reliance on mortgage lending. The underperformance is concentrated in the sample of small banks. While these banks have smaller balance sheets, they are not only active in a single county or even state but across several borders, which renews the importance of capturing the total exposure using a bank's balance sheet information.

I extend the analysis of flood risk in the cross-section of bank stock returns by sorting banks into portfolios based on their flood risk exposure. A portfolio of banks with high exposure to flood risk exhibits lower future returns than stocks with low exposure. An exposure-weighted portfolio that goes long the top quartile portfolio and shorts the lowest flood risk quartile underperforms by 43 basis points (bps) per month or 5.2% per year.[7] The results are similar for value-weighted portfolios. When only analyzing small banks, the flood risk discount increases to 77 bps per month, or over 9% annualized. The negative alpha cannot be explained by controlling for the four equity factors from Carhart (1997), and two bond factors from Gandhi and Lustig (2015). I use the portfolio return to create a tradeable flood risk factor by subtracting the portfolio returns of the bottom quartile from the portfolio returns of the top quartile. Rebalancing yearly, over the period from 2004 to 2020, the factor lost around 50% in the entire sample of banks, or 80% when focusing on small banks.

The systematic flood discount is puzzling. If the risk exposure is priced, expected returns on exposed banks should earn a premium, or at least, there should not be a discount, as investors may require higher expected returns from firms with higher risk exposure to flooding. Past return performance may diverge from expected returns for different reasons. Counties with a high flood probability correlate with counties experiencing flood disasters. Thus, bank-level flood risk exposure could be picking up an omitted disaster variable, which could explain the estimated lower return performance. I perform three tests to examine whether realized flood disasters explain underperformance. First, the flood discount captured by the flood risk exposure prevails in a sample without periods of significant floods and storms. Even when removing all months with floods of any size, the underperformance on the flood risk exposure remains. The magnitudes of the coefficients on the flood risk exposure are slightly smaller (1.5 pp discount versus 2.4 pp in the baseline). Second, the underperformance of flood risk exposed banks persists even when explicitly controlling for past disasters using the property damage estimates. Third, underperformance prevails when using disaster-adjusted returns as dependent variables. Across the three tests, controlling for past flood disasters reduces the coefficient of flood risk exposure; however, the relation between flood risk and excess returns remains negative and significant. The finding suggests that another driver than flood disasters likely

[7] To compute exposure-weighted portfolio returns, the flood risk exposure is first standardized to a zero-mean.

explains the negative relation. Consistent with findings from the first part of the paper, flood damage exposure predicts lower excess returns.

The period from 2004 to 2020 also coincides with an essential change in assessing climate change-related risks from the perspective of investors and the public in general. Recent studies have found that this transition period can explain differences in expected and realized returns for stocks of climate risks exposed firms (e.g., Pástor, Stambaugh, and Taylor, 2021). As investors' preferences for assets less exposed to climate risks increase, prices of low-risk assets can outperform riskier assets. I test whether the observed increase in climate change concerns coincide with the flood risk exposure and can explain the underperformance of the flood risk-exposed banks. While climate change concerns measured by climate change attention data from Google and (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022) are also linked to lower excess returns consistent with prior findings, the concern proxies cannot explain the negative coefficient on the flood risk exposure.

Finally, I perform a series of robustness tests. While the primary flood risk measure is based on flood probability by 2050, the main result is robust to alternative measures such as county-level average risk scores or shorter-term projections. The result also holds when constructing the bank-level risk measure using the number of retained mortgages instead of retained amounts or mortgage originations, which suggests that outliers in the data do not drive the finding. Furthermore, the results persist when controlling for differences in the local flood insurance measured from data from FEMA's National Flood Insurance Program (NFIP), covering 95% of the flood insurance activity in the United States. Controlling for state-level changes in GDP, unemployment rate, and inflation allows me to rule out that the flood risk exposure measures local economic activity. Similar results are obtained when controlling for local mortgage delinquencies and foreclosure exposures. Furthermore, including indicator variables for the fifty states and headquarter fixed effects do not change the results.

This paper is most closely related to the literature investigating the pricing of climate risk, generally in equities. Examples include Bolton and Kacperczyk (2021), Bolton and Kacperczyk (forthcoming), Duan, Li, and Wen (2021), Hsu, Li, and Tsou (2021). All these papers focus on the transition risk from climate change. At the same time, this study examines the physical risk from climate change, such as Hong, Li, and Xu (2019) who find that stocks under-react to the long-term risk of drought; Acharya, Johnson, Sundaresan, and Tomunen (2022) that find that exposure to heat stress commends higher returns in the cross-section of stock returns; or Choi, Gao, and Jiang (2020) who show that stocks of carbon-intensive firms underperform when temperatures are abnormally high. This paper analyzes the risk of flooding for the banking sector.

The evidence on how flood shocks affect realized returns also relates to Pástor, Stambaugh, and Taylor (2021), who show that green assets can outperform brown assets when climate concerns increase. Using *The Wall Street Journal*, Engle, Giglio, Kelly, Lee, and Stroebel (2020) build a Climate News Index and use it to construct a portfolio that hedges climate change risk. Extending this to negative concerns from climate change, Ardia, Bluteau, Boudt, and Inghelbrecht (2022) create another word-based index. I document that climate change concerns cannot explain the results in this paper.

Next, the paper contributes to the literature on natural disasters and bank operations. This literature has so far only focused on the effect of past disasters on banks, while the main focus of this paper is to analyze the effect of risks from physical costs from climate change. Specifically, the analysis in this paper is for future flood risk materializing in the next 30 years and therefore is forward-looking. The evidence from the literature suggests that affected banks increase their lending in affected areas following disasters (e.g., Cortés and Strahan, 2017; Barth, Sun, and Zhang, 2019; Bos, Li, and Sanders, 2022; Koetter, Noth, and Rehbein, 2020; Brown, Gustafson, and Ivanov, 2021; Ivanov, Macchiavelli, and Santos, 2022). Ouazad and Kahn (2021) argue that commercial banks pay attention to climate risk once it hits. They find that following disasters, banks are more likely to load off their mortgages by selling them to the two government-sponsored enterprises (GSE), Fannie Mae and Freddie Mac, while Garbarino and Guin (2021) find that home loan lenders do not adjust their valuation, loan amounts, nor mortgage interest rate following an episode of severe flooding. The findings of this literature flow into the analysis in this paper by looking at securitized mortgages separately.

The effect on the bank's performance is also less clear from the existing literature. Schüwer, Lambert, and Noth (2019) and Blickle, Hamerling, and Morgan (2021) find a positive or insignificant effect on performance, while Noth and Schüwer (2018) provide evidence that return on assets decreases and non-performing loans (NPL) increase. The common approach in this literature to measure banks' exposures to natural disasters has been to use branch locations. In this paper, I show the importance of using a bank's full balance sheet to measure a bank's exposure to shocks. Specifically, I use banks' mortgage lending activity and argue that this matches actual exposure more closely. I show that flood hazards matter for bank performance if a bank's exposure is measured by its mortgage lending activity while focusing on branch location cannot capture the link.

The paper uses results from the literature studying the effect of weather hazards on real estate markets. Some papers find no clear price discount for flood-exposed homes (e.g., Murfin and Spiegel, 2020; Keys and Mulder, 2020; Gibson and Mullins, 2020), while others find that houses at risk of flooding trade sell at a lower price, but only for specific types of households (e.g., Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021). Overall the results in this literature suggest that not all risk from flooding is priced in the residential real estate market.

Finally, my paper contributes to the literature on bank risk factors. In a multi-factor framework that includes real estate risk, Bessler and Kurmann (2014) show that bank risk exposures are multi-dimensional and time-varying. Gandhi and Lustig (2015) focus on a size anomaly specific to the banking sector. Meiselman, Nagel, and Purnanandam (2020) find evidence that bank profits predict future stock returns. I add a new risk factor based on flood exposure to this literature.

The remainder of the paper is organized as follows. Section 2 describes the data and introduces the main explanatory variables. Section 3 analyzes the costs from realized floods to banks. Section 4 shows that the flood risk exposure predicts lower returns in the cross-section of bank stock returns. Section 5 discusses economic mechanisms of underperformance. Section 6 shows that the patterns are robust to an array of additional controls. Finally, Section 7 concludes.

2. Data and Summary Statistics

This section describes the different data sources and introduces the key explanatory variables. The focus of this paper lies on floods and hurricanes among natural disasters. They represent the costliest disasters in the United States (Davenport et al., 2021). Since 2000, floods and storms resulted in almost \$300bn in property damages (Figure 1). And they account for over three-quarters of the estimated property damages caused by all types of natural disasters in the US, as shown in Figure 1b. While the yearly average amount of damage from floods and hurricanes has already strongly increased over the last couple of decades, sea level rise and climate change are projected to drive up damages even further (Davenport et al., 2021).

As pointed out by the ECB (2019), with increases in frequency and severity of climate disasters, the risk of abrupt value losses of assets in climate risk-sensitive geographical areas increases. Real estate is inextricably linked to its geographic location. Therefore housing in exposed areas is likely to be negatively affected by the expected increase in natural disasters. For financial institutions lending to this area, this implies that collateral and asset values become riskier. Every year, mortgage lenders originate between \$200 and \$250 billion in new mortgages in flood zones, representing roughly 10% of total bank equity (Ouazad, 2020), which means potentially large financial losses.

To test the link between bank performance and flood disasters, I require estimates of property damages from floods. And to test for the existence of a flood risk premium, I use regional probabilities of flooding that are combined with a bank-level county weight measure based on mortgage lending data to create novel flood risk exposures. On average, the final data contains information from 400 bank holding companies (BHC) covering 2004 to 2020.

[Place Figure 1 about here]

2.1. Bank-Level County Weights

To compute the geographic exposure measure at the bank holding company level, I use data on U.S. mortgages obtained from the publicly available part of the data filed under the Home Mortgage Disclosure Act (HMDA). Federally insured or regulated depository institutions with total assets exceeding $45 million are required to report the received mortgage loan applications and decisions at a yearly frequency.[8] However, as the analysis primarily focuses on publicly listed banks, which typically are large, there is no reason to expect that this threshold and feature of the data should systematically bias the findings.

HMDA is mortgage application-level data and includes detailed information on the mortgage. Importantly, the data contains information about the status of the application (e.g., accepted). The data typically covers over 90 percent of the annual mortgage activity (Favara and Giannetti, 2017). This study focuses on conventional loans and one- to four-family home purchase loans that originated because bankruptcy and foreclosure laws, as well as government bailout programs, differ for larger dwellings (Bongaerts et al., 2021). The data is further restricted to owner-occupied houses (Ouazad and Kahn, 2021). Non-owner occupancies are assumed to be more sophisticated borrowers who are more likely to insure themselves against flood risk.

2.2. Flood Damages

Flood disaster shocks are constructed using data from Spatial Hazard Event and Losses Database for the United States (Sheldus) maintained by the University of Arizona.[9]The data provides information on the date, location, and intensity of all presidentially declared natural disasters in the US. For this study, the data is restricted to major floodings and storms. While the National Oceanic and Atmospheric Administration (NOAA) also collects information on non-presidentially declared natural disasters, Sheldus has the advantage of estimating dollar damages linked to the different disasters. Additionally, presidentially declared disasters are more likely to be severe and represent significant shocks to banks (Ivanov et al., 2022). I measure the intensity of a flood disaster using the total dollar value of property damages in a given county and quarter. An alternative shock measure is an indicator variable that captures the extreme tail events.

[8] The $45 million threshold was set in 2018. Typically, it is time-varying and set by the Consumer Financial Protection Bureau. Additionally, only banks that originated at least one home purchase loan or the refinancing of a home purchase loan with an office in a metropolitan statistical are required to report.

[9] The data is available for download from the Center for Emergency Management and Homeland Security (2018) under `https://cemhs.asu.edu/sheldus`.

2.3. Expected Flood Risk

To test the existence of a flood risk premium, I require a comprehensive map defining the geographic distribution of flood probabilities in the contiguous United States. For this purpose, I use a relatively new map produced by the First Street Foundation. The data provides information on the share of housing with a 1% probability of experiencing a 100-year flood in the cross-section of US counties. The estimates consider increased risk from sea-level rise and changes in weather patterns. I use this alternative over the more widely used flood maps produced by FEMA because FEMA maps are shown to be outdated. The maps produced by the First Street Foundations cover more counties and use an up-to-date methodology compared to maps provided by the FEMA. The number of properties with a substantial risk of flooding is approximately 70% higher than what is estimated by FEMA's maps (Flavelle, Lu, Penney, Popovich, and Schwartz, 2020). In addition, estimates show that 80% of commercial properties damaged by Hurricane Harvey and Hurricane Irma were outside FEMA-designated flood zones (Duguid and Levine, 2020) Therefore, the maps from FSF represent a better measure of the underlying flood probability of a county.

Furthermore, the advantage of using these maps as compared to sea level rise maps (e.g., Ilhan, 2021) is that they cover the whole United States, which allows capturing banks only active in landlocked regions. To my knowledge, I am the first to link these flood maps to regional bank activity.

[Figure 2 about here]

The key variable is shown in Figure 2. It represents the share of properties with a 1% probability of a 1-meter flood by 2050 for each county in the continental United States. Darker shades of blue represent a larger share. Unsurprisingly, coastal regions are expected to be the most affected. Still, counties in lower areas of the Northwest and counties in the Appalachian are also projected to be of high risk.

2.4. Bank Outcomes

Bank balance sheet data comes from the quarterly Consolidated Report of Condition and Income (FR Y-9C) filed by US BHC with the Federal Reserve. The data includes information on bank size and profitability.

Equity returns are from the monthly stock file from the Center for Research in Security Prices (CRSP), which includes monthly returns and prices. In this section, I focus on bank holding companies.

2.5. Measuring Banks' Exposures to Floods and Flood Risk

Bank profitability may be directly or indirectly affected by changes in weather patterns. More severe flood disasters eventually lead to increasing household delinquencies and defaults, ultimately affecting banks' income and profitability. Alternatively, sudden decreases in the value of a collateral lead to readjustments in household behaviors such as borrowing and consumption (Mian and Sufi, 2011), which may affect a bank's general economic performance in that region. Further, mortgage-backed securities are also more likely to be written-offs. Given the mixed evidence that banks account for the risk from disasters in their lending decisions (e.g., Garbarino and Guin, 2021), banks remain exposed to the risk - at least to a non-negligible part. There is some evidence that banks exposed to flood disasters increase the securitization of mortgages (Ouazad and Kahn, 2021). The empirical analysis accounts explicitly for this possibility by focusing on non-securitized mortgages.

The analyses in this study focus on bank-level outcomes such as stock returns or return on assets, while the shocks and probabilities used as explanatory variables are available at the county level. Therefore, the county-level variables have to be aggregated at the bank level. An important aspect of this step is carefully considering the relevant exposures for a given bank. A common approach in the literature has been to use bank headquarters or branches as a measure of regional bank exposure. The shortcoming of this approach is that banks typically lend outside of the counties where they are physically present. Further, banks are assumed to be exposed to flood risks and disasters through their asset holdings. I introduce a novel county weight of each bank based on a bank's mortgage lending activity. Specifically, using HMDA, I compute the exposure as total originated home loans retained on the balance sheet by county divided by the overall yearly originated mortgages retained on a bank's balance sheet. Equation 1 formalizes this:

$$County\ Weight_{b,c,y} = \frac{\sum_y Retained_{b,c,y}}{\sum_c \sum_y Retained_{b,c,y}}, \tag{1}$$

where $Retained_{b,c,t}$ is the total amount of mortgages originated and retained in county c and year y by bank b. A mortgage is defined as retained if it is not securitized or sold to a third party. As I wish to capture banks' exposure to a county, I focus only on mortgages retained in the banks' portfolios. Additionally, banks have been shown to react to flood disasters by securitizing more of their mortgage issuances (Ouazad and Kahn, 2021). Ultimately, this reduces the bank's exposure to negative shocks to collateral values. In robustness tests, I show that the results also hold if the full amount of originated mortgages is used. Additionally, I perform a placebo test by constructing the measure only using sold or securitized mortgages.

To analyze how a bank's balance sheet performance is affected by flood disaster shocks, I combine the county-level exposure with the county-level property damage estimates from Sheldus. Formally, I have:

$$\text{(2)} \qquad \textit{Damage Exposure}_{b,q} = \sum_{c} (\textit{County Weight}_{b,c,y} \times \textit{Property Damage}_{c,q}).$$

The damage exposure can be viewed as a weighted average of the damages that occurred in quarter q.

Finally, to test whether the exposure to the risk of flooding is priced in the cross-section of bank stock returns, I create a bank-level flood risk exposure by weighing the share of properties with a high flood probability with the bank's county weight. Formally, I have equation 3:

$$\text{(3)} \qquad \textit{Flood Risk Exposure}_{b,y} = \sum_{c} (\textit{County Weight}_{b,c,y} \times \textit{Flood Probability}_{c}),$$

where *Flood Probability* is the flood probability measure from the flood maps produced by FSF. In robustness tests, I alternatively use the county-average risk measure and the share of properties at risk by 2035. In addition to using different flood risk measures, I control the robustness of the finding by using additional weight measures (i.e., the retained mortgage share): namely, the number of retained mortgages instead of amount, total originated amount and rolling averages of retained and originated mortgages. Rolling averages alleviate concerns that outlier exposures in mortgage lending drive the results. Additionally, rolling averages arguable capture underlying lending patterns more closely than yearly flow measures. They are a better proxy for future lending patterns (Favara and Giannetti, 2017). Therefore, they capture the broad exposure to future profits from lending to a specific county by a given bank.

2.6. Summary Statistics

Table 1 reports the summary statistics and differences between banks with high exposure to flooding risk and banks with low exposure to flood risk. *High* risk banks are defined as banks within the top quartile sorted on the flood risk exposure each year, while *Low* are all other banks. Mortgage-based variables change at an annual frequency. *Application* is the total dollar amount of mortgage loan applications received by a bank in a given year. *Retained Amount* is the total dollar amount of mortgages originated and retained by a bank in a given year. This measure excludes non-originated applications and originated mortgages that were either securitized or sold to a third-party financial firm. *Active Counties* and *Active Census* is the total number of unique counties and states in which a bank originated mortgages. *Average Originations* and *Average Retained* are county-level dollar amounts of originated and retained mortgages averaged across all active counties for a given bank in a given year. As a sanity check, the two groups differ significantly along the key measures of flood risk exposure. Depending on the measure, high flood risk banks have up to 3 times more mortgages in high-risk counties than low-risk banks. Within mortgage variables, banks along the flood risk exposure measure are reasonably similar. On average, they receive and retain equal amounts of mortgage applications. Less exposed banks tend, on average, to be active in slightly more counties and across more states. Stock variables are based on monthly stock returns. Balance sheet variables from the Call Reports are updated at a quarterly frequency. Ratios are calculated by dividing by total assets. *Loan Ratio* is the sum of consumer, commercial, and industry loans divided by total assets is the loan ratio. *Real Estate Loans Ratio* is the sum of retail and commercial loans, while *Mortgage Ratio* is calculated using only retail mortgage loans. *ROA* is net income divided by total assets. *NPL Ratio* is calculated by dividing the sum of 30 and 90 days delinquent loans by total assets. From the table, it also becomes apparent that the two groups differ along some important variables. They are smaller on average and therefore are more focused on mortgage lending. They also rely more on deposit funding. Notably, on average, they do not differ in profitability, the share of non-performing loans, or leverage ratio. In the later sections, I will account for the observed differences by performing different subsample analyses.

[Table 1 about here]

3. The Cost of Flood Disasters

In this section, I analyze the cost of flood disasters for banks measured by different outcomes. First, I will illustrate the link between flood disasters and bank returns by focusing on a major and well-known disasters, Hurricane Katrina. Second, the analysis will focus on the balance sheet performance of the largest sample of banks (i.e., including subsidiaries and non-publicly traded). Third, I restrict the sample to publicly traded banks, because the existence of a flood risk premium is tested on this sample.

3.1. Hurricane Katrina

Hurricane Katrina was the largest flood disaster in the U.S. in the last twenty years. Estimates from the Bureau of Labour Statistics show that industrial production decreased by 12.6% with approximately 230 thousand job losses. As the intensity of the storm became clear, markets priced the potential exposure to the damages.

The methodology involves plotting the cumulative abnormal return (CAR) of the portfolio of banks only active in counties affected by the hurricane (i.e., the treated) and comparing it to the CAR of banks active in unaffected counties (control). Formally, I calculate the abnormal return of each bank as follows:

$$AR_{bt} = R_{bt} - E[R_{bt}]. \tag{4}$$

The daily expected return is defined as

$$E[R_{bt}] = \hat{\alpha}_b + \hat{\boldsymbol{\beta}}_{\boldsymbol{b}}' \boldsymbol{F},$$

where $\boldsymbol{F}$ is a vector of factors (Market, SMB, HML, ΔVIX), and the coefficients $\hat{\alpha}_b$ and $\hat{\boldsymbol{\beta}}_{\boldsymbol{b}}$ are estimated on daily data from January 1 2005 to July 31, 2005, by regressing the bank-level return on the market factors. Formally, I estimate the following time-series equation for all banks in the sample:

$$R_{bt} = \alpha_b + \boldsymbol{\beta}_{\boldsymbol{b}}' \boldsymbol{F} + \epsilon_{bt}.$$

I follow Schüwer et al. (2019) to classify banks as affected or treated. Following major disasters, FEMA designates counties as eligible for individual and public disaster assistance.[10] During the hurricane season of 2005, 135 of the 534 counties in the Gulf Coast region were designated to be eligible for FEMA's disaster assistance. A bank is affected by Hurricane Katrina if all its mortgage lending in the previous year (2004) was for properties located in a county eligible for individual and public disaster assistance (the orange region in Figure 3a). The control group consists of banks with all their mortgage lending in counties that received neither individual nor public disaster assistance but are located in the U.S. Gulf region or a neighboring state.[11] These counties are shown in dark blue in Figure 3a. Counties that only received public assistance are excluded. As pointed out in Schüwer et al. (2019), some counties received public assistance because they housed evacuees but were not directly negatively affected by damages. Consequently, nineteen banks are cleanly identified as only active in affected counties, and 27 are located in unaffected counties.

Figure 3b plots the daily cumulative abnormal return of the two value-weighted portfolios from July 2005 to October 2005.

Hurricane Katrina formed on August 24. In the following days, the storm's intensity and trajectory became more apparent. On August 26, it went over the southern tip of Florida, and the trajectory was revised to the Mississippi coast (United States Department of Commerce, 2006). This is seen in the first days of lower negative abnormal returns

[10] See https://www.fema.gov/disasters.

[11] The U.S. Gulf States are Alabama, Florida, Louisiana, Mississippi, and Texas. Arkansas, Georgia, Oklahoma, and Tennessee are the neighboring states.

compared to the control group. On August 28, the National Weather Service issued a statement that Hurricane Katrina is a "most powerful hurricane with unprecedented strength" and that "most of the area will be uninhabitable for weeks" (National Weather Service New Orleans, 2005). The storm made landfall on August 29, and the CAR of affected banks dropped by almost 15% in a matter of days. This is equal to a $4.5bn loss in market capitalization of affected banks. Interestingly, abnormal returns remained negative for a considerable time, and the CAR never recovered over the sample. This shows that markets react to the risk from natural disasters once the risk materializes and salience is high. While banks in the control group are also active in the extended coastal region, only the abnormal return of ex-post-affected banks decreased. This points to evidence that markets correctly identify the banks' exposures when faced with a disaster.

[Figure 3 about here]

3.2. Shock to Balance Sheet

This section focuses on bank performance following major flood disasters. The empirical analysis involves regressing bank outcomes on the measure of exposure to flood damages introduced in Section 2. Formally, I estimate the following equation:

$$\begin{aligned} Y_{bt} = \beta_0 &+ \beta_1 \mathit{Flood\ Damage\ Exposure}_{bt-1} + \beta_2 \mathit{Capital\ Ratio}_{bt-1} \\ &+ \beta_3 \mathit{log(Employees)}_{bt-1} + \beta_4 \mathit{log(Assets)}_{bt-1} \\ &+ \beta_5 \mathit{ROA}_{bt-1} + \boldsymbol{\gamma X} + \epsilon_{bt}, \end{aligned} \tag{5}$$

where Y_{bt} represents the outcome of interest, such as return on assets, capital ratio, or non-performing loans. The regression includes a standard set of bank-level control variables. Further, the regression includes time (quarter) and bank fixed effects, given by the vector of $\boldsymbol{X}$. The bank fixed effects ensure that results are unlikely to be driven by unobserved lender characteristics, while the time fixed effects alleviate concerns that the results are driven by specific periods. Standard errors are clustered at the bank holding company.

[Table 2 about here]

Panel A of Table 2 reports estimates of equation 5 for bank-level return on assets. The regression in column (1) has no fixed effects. Time-fixed effects are added in column (2), while column (3) includes both time and bank-fixed effects. Comparing coefficients shows that the inclusion of fixed effects has little effect on the magnitude and significance.

Across the three specifications, I find a negative and statistically significant relationship between the exposure to flood damages and return on assets. The variable *Flood Damage*

Exposure has a t-statistic between -3.8 and -2.3. The variable *Flood Damage Exposure* has been standardized for ease of interpretation. Therefore, the coefficient of -0.004 in column (3) suggests that a one-standard-deviation increase in flood damage exposure results in a decrease in quarterly return on assets of 0.4 basis points. Given an average of 0.4%, this is equal to a 1% decrease in the average return on assets. However, the distribution of flood disasters typically has a large right tail. Hurricane Katrina had a magnitude of almost 100 standard deviations, wiping out almost the entire income of affected banks. This shows that large shocks are plausible (and likely). A ten-standard-deviation increase in flood shocks is associated with returns on assets of affected banks being 10% lower, consistent with flood damages having a potentially important negative effect on bank performance. This finding is evidence that banks remain exposed to flood disasters, and by extension, to the risk of flooding.

This finding is in contrast to Blickle et al. (2021), who find that bank performance is not negatively affected by natural disasters. Their analysis relies on computing the exposure measures using bank branch information, either by using the number of branches in a county or the share of deposits in a county. I argue that banks are exposed through their asset holdings. An exposure measure to natural disasters should therefore reflect a bank's asset side instead of its liabilities. Furthermore, and more importantly, a bank is assumed to be exposed through its mortgage loan portfolio. Finally, banks typically extend loans outside of their home counties. Hence focusing on physical bank location potentially omits important exposures. Panel B of Table 2 provides evidence of this. The results are obtained from the same regression (equation 5) but using two different exposure measures. In column (2), instead of using mortgage-weighted exposure, county-level flood damages are aggregated using deposits as weights. In contrast, column (3) weighs by physical office locations.[12] The coefficients of interest are insignificant in both cases. This additional test helps reconcile the findings in this study with the findings in prior studies (e.g., Blickle et al., 2021).

The baseline *Flood Damage Exposure* is constructed using damage amounts in dollars. One might be worried that the results capture underlying differences in exposure. Given a same-sized shock, wealthier counties will likely experience higher damage amounts because affected homes have a higher value. To rule out that this is driving the results, in column (1) of Panel B of Table 2, the dependent variable is redefined as the total property damages divided by the county-level total personal income. In this context, the coefficient is of similar magnitude as in the baseline results, suggesting that wealth differences are not driving the results.

[Table 3 about here]

[12]Branch locations and branch-level deposits come from the FDIC Summary of Deposits.

Table 3 reports the results from equation 5 for a set of balance sheet variables of the publicly traded bank holding companies.[13] All regressions control for time-varying bank characteristics such as leverage, assets, loan ratio, and mortgage ratio. As previously, bank and time fixed effects are included in the regression, while standard errors are clustered at the bank holding company. Column (1) replicates the baseline results for return on assets. The coefficient on *Flood Damage Exposure* has the same sign and very similar magnitude as in Panel A of 2, suggesting that the effect is propagated at the bank holding company. A large flood disaster is associated with exposed banks performing 10% worse than unaffected but otherwise comparable banks. Columns (2) and (3) focus on prudential capital requirements. The estimates show that leverage and capital ratios decrease when flood damages increase. A one-standard-deviation increase in flood damages reduces the ratios by approximately 2 bps. However, given average ratios between 8% and 14%, the effect is small, even for larger episodes. Nevertheless, the coefficients are statistically significant, with t-statistics below -2.56. The net stable wholesale funding ratio also declines by 5 bps after a one-standard-deviation increase in flood damages, as reported in column (4). The estimates suggest that banks not only have lower profits but experience losses on their equity. However, the reduced ROA is not matched one-to-one with a reduction in equity, implying that banks manage to offset the majority of the shock without loss on their equity.

Column (5) reports the estimates from a regression of the *Z-score*, defined as

$$Z\text{-}score_{bt} = \frac{roa_{bt} + equity_{bt}}{\sigma(roa_{bt})},$$

where $\sigma(roa_{bt})$ is the standard deviation of returns on assets. The *Z-score* proxies for the distance-to-default of a bank. The coefficient on *Flood Damage Exposure* in column (5) is negative and significant. The estimate implies that the distance to default is negatively associated with flood disasters and is consistent with flood damages increasing the default likelihood of a bank.

The results in columns (6) to (7) are based on loan performance variables. The effects on non-performing loans, residential real estate loan charge-offs, and loan-loss provisions are positive, albeit only significantly so in the last case. The coefficients provide suggestive evidence that the performance of loans decreases following flood disasters and that flood disasters indeed lead to poorer loan performance and, therefore higher loan losses.

[13] From this point onward, I refer to publicly-traded bank holding banks simply as banks or BHCs.

3.3. Effect Heterogeneity

The summary statistics have shown significant heterogeneity on some dimensions between banks with high and low exposure to flood risk. Therefore, *Flood Damage Exposure* likely has heterogenous effects on performance variables. Small banks in the sample are typically less diversified (Laeven and Levine, 2007) and have more geographically concentrated lending (Doerr and Schaz, 2021). Further, the propensity to securitize mortgage loans differs between small and large banks (Casu et al., 2013). Smaller banks offload less of their riskier loans to third parties through securitization. Therefore flood disasters affect smaller banks to a more significant extent than bigger banks. Similarly, banks more active in mortgage lending, that is with a higher fraction of mortgage loans on their balance sheet should be more affected than banks specializing in other activities.

To examine this heterogeneity, Table 4 presents separate estimates of equation 5 for banks with a high share of mortgage lending (High) compared to banks with a lower share of mortgage lending (Low), and small banks compared to large banks. The partitioning is based on the median mortgage lending share and size, respectively. All regressions are robust to bank controls, and bank and quarter fixed effects.

[Table 4 about here]

Panel A of Table 4 reports the results for the return on assets for the four groups. Columns (1) and (2) split the sample on the mortgage loan share, while the results in columns (3) and (4) compare small and large banks. The magnitude of the coefficient of the $High$ mortgage loan share is somewhat larger than for the *Low* sample, consistent with the assumption that the transmission of flood disasters to bank performance is through mortgage loans. Comparing the coefficients across size-sorted samples, if anything, the magnitude of the larger banks is bigger, suggesting that the return on assets of larger banks reacts more to flood shocks than the ROA of smaller banks. This is surprising given that larger banks are, on average, less exposed to flood zones and are more geographically diversified.

The full-sample results from Table 3 implied an insignificant relation between flood damages and non-performing loans. The subsample analysis shows that NPL and loan charge-offs of banks with a larger share of mortgages on their balance sheet are positively associated with an increase in flood damages. I find no significant relation between flood damages and loan performance variables for banks with a low share of mortgages on their balance sheet. The coefficients suggest that this does not appear to be due to a lack of statistical power, as the coefficients are statistically insignificant and smaller in magnitude.

Surprisingly, when focusing on small and large banks separately, the estimates show that a significant effect on NPL is unique to the sample of larger banks. The non-performing loan ratio increases after flood damages only for large banks. Specifically, I find no evidence that the sample of small banks incurs an increase in their non-performing loans - if anything, the NPL ratio is lower for small banks exposed to a shock. Within the sample of large banks, the estimates show that the NPL ratio is 10% higher following a one-standard-deviation flood shock. The finding is insofar remarkable because larger banks are more diversified and typically have more tools at their disposition to weather natural disasters (Cortés and Strahan, 2017). However, the finding could also show that larger banks accept higher non-performing loans in the short term to avoid larger loan losses or charge-offs. Panel C of Table 4 offers a first answer: there seems to be no increase in loan charge-offs for either sample of banks. The relation between flood damages and loan charge-offs is insignificant for large and small banks.

3.4. Persistent Effects

The previous section focused on one-quarter ahead performance variables. Natural disasters, such as floods, arguably have longer-lasting effects, or more precisely, the effects might only be registered later on banks' balance sheet items. Household delinquencies and defaults only materialize with a lag, as I will show.

The empirical strategy involves regressing bank outcomes in periods $t + h$ on the measure of exposure to flood damages introduced in Section 2. Formally, I estimate the following equation:

$$\begin{aligned} Y_{bt+h} = \beta_0 &+ \beta_1^h \mathit{Flood\ Damage\ Exposure}_{bt-1} + \beta_2^h Y_{bt-1} + \beta_3^h \mathit{Capital\ Ratio}_{bt-1} \\ &+ \beta_4^h \mathit{log(Employees)}_{bt-1} + \beta_5^h \mathit{log(Assets)}_{bt-1} \\ &+ \beta_6 ROA_{bt-1} + \boldsymbol{\gamma X} + \epsilon_{bt}^h, \end{aligned} \tag{6}$$

where h goes from -3 to $+4$ quarters. I report the coefficients β_1^h on *Flood Damage Exposure* for the two bank performance variables, return on assets and Tier 1 leverage ratio, in Figure 4. In both panels, the solid line (with circles) presents the point estimates of β_1^h from equation , and the dashed lines (with triangles) present the 95% confidence intervals on this estimate. Standard errors are clustered at the bank level.

Figure 4a shows the long-run effect of flood damages on bank-level return on assets. The quarter 1 coefficient is the same as the coefficient in column (1) of Table 2. The plot shows that the drop in return on assets starts in the same quarter as the flood disaster and tapers off over the next year, consistent with the effects of floods having longer-term consequences. Further, the finding indicates that most of the effect on profitability occurs in the same quarter as the flood realizes. The finding is echoed in Figure 4b, which plots the coefficient of Tier 1 leverage on flood damages. Again, most of the effect occurs between the first and the second quarter after the flood disasters. Because the points on the line estimate cumulative effects on the leverage ratio since the shock, the flattening of the line after the second quarter suggests that the flood has little impact on leverage in the second half of the year after the disaster. That leverage remains significantly below its pre-flood level is surprising. Banks might either choose not to or are unable to increase their capital. Either way, it demonstrates that banks are significantly riskier after experiencing major natural disasters, as had also been conveyed by the significantly lower Z-score. This result emphasizes the long-lasting effects of a natural disaster (Noth and Schüwer, 2018). The coefficient estimates in both plots do not show any significant pre-trend.

The evidence in Panel A and B of Figure 4 is consistent with banks experiencing significant losses from floods that require them to offset losses with their equity.

[Figure 4 about here]

Figure 5 conducts a similar analysis using two loan portfolio variables as the outcomes of interest. As seen in Section 3.3, the effect on portfolio performance variables is only seen in the subsample of banks with a high share of mortgage loans on their balance sheet. As previously, the solid line (with circles) presents the point estimates of β_1^h from equation , and the dashed lines (with triangles) give the 95% confidence intervals on this estimate. Standard errors are clustered at the bank level. The flood realizes at time 0. The coefficients are insignificant for the periods before the shock. Figure 5a plots the coefficient from regressing the non-performing loans ratio on flood damages for the sample of banks with a high share of mortgages. Following the shock, the coefficient is positive and implies an increase in non-performing loans within the sample of banks with a high share of mortgages. As previously, the picture suggests that the full effect of the disaster is only registered after some time. The share of non-performing loans increases for three quarters before slowly reverting. Given that non-performing loans are typically measured as loans with missed payments after thirty to ninety days, the insignificant effect in quarter 0 is comforting. It bolsters the identifying assumption that borrowers do not adjust their repayments in anticipation of future adverse weather shocks. Similarly, as shown in Figure 5b, loan charge-offs increase in the quarter following the shock and remain elevated for the next couple of quarters. The increase in loan charge-offs is steeper than the increase in non-performing loans. While NPLs depend on borrowers' behavior, charge-offs are set by lenders. So the difference in slope suggests that lenders partly anticipate the increase in NPL and the ensuing default of a number of borrowers.

Taken together, the evidence Figure 4 and 5 is consistent with banks' balance sheets deteriorating significantly after flood disasters and that the effect manifests itself over a relatively long period.

[Figure 5 about here]

4. Exposure to Flood Risk

The previous section demonstrated that flood disasters are negatively linked to bank performance, both measured by return on assets and stock returns. In this section, I examine whether the stock market prices the exposure to flood risk in the cross-section of returns.

Specifically, the conjecture is that investors may require higher expected returns from banks with high exposure to the risk of flooding. First, I run cross-sectional regressions to test whether the exposure matters at the individual bank. Additionally, this allows to rule out other known risk factors and characteristics predicting returns in the cross-section and ensures the novelty of the flood risk exposure. We have seen that bank size matters in the transmission of flood disasters. So second, the potential heterogeneous effects in the flood risk premium are analyzed separately.

4.1. Evidence in the Cross-Section of Returns

The benefit of cross-sectional regressions is that they allow for controlling for multiple characteristics jointly. To do so, bank-level excess returns are regressed on lagged flood risk exposures and additional characteristics. Formally, the following cross-sectional regression model using pooled OLS estimated:

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 \textit{Flood Risk Exposure}_{bt-1} \\ &+ \beta_2 \textit{log(Assets)}_{bt-1} + \beta_3 \textit{log(BE/ME)}_{bt-1} \\ &+ \beta_4 \textit{Leverage}_{bt-1} + \beta_5 r_{bt-1} + \epsilon_{bt}, \end{aligned} \tag{7}$$

where the dependent variable is the stock return of BHC (b) over the risk-free rate in month t. The main coefficient of interest is β_1 on the *Flood Risk Exposure* that captures a bank's balance sheet exposure to flood risk. A positive β_1 coefficient would imply that an increased exposure earns a positive risk premium. By the focus of the analysis, standard errors are clustered at the bank level. Aggregate time-varying factors are absorbed by the month-fixed effects. The coefficient of interest is β_1.

Column (1) of Table 5 reports the baseline result with the exposure measure based on flood probabilities in 2050 and the share of retained mortgages. The coefficient on the flood risk measure is negative and statistically significant at the 1% level. The effect is also economically significant: a one-standard-deviation increase in flood risk measure leads to a 17-bps decrease in monthly stock returns, or 2% annualized. The estimate suggests that a high flood risk exposure forecasts poor stock performance. Overall, the results imply firms with high flood risk exhibit lower future excess returns net of well-known bank characteristics. This finding is in line with other papers testing whether markets discount physical risk from climate change (e.g., Hong, Li, and Xu, 2019), and highlights differences to studies focused on transition risks from climate change that typically find that investors require higher expected returns from firms with higher risk exposure (e.g., Bolton and Kacperczyk, 2021).

[Table 5 about here]

The result is robust to different measures of flood risk exposure. Columns (2) to (7) report the results for six different flood risk exposure measures that capture very similar effects. In column (2), the exposure measure is based on a shorter flood horizon, specifically 2035 (instead of 2050). The regression in column (3) is based on an exposure measure using flood risk scores instead of the share of houses at risk. Column (4) weighs the underlying flood risk by the number of retained mortgages instead of the dollar amount. In column (5), all originated mortgages in a county are used to build the county weights. The main measure of flood risk exposure is purely based on the flow of new retained mortgages. This approach is prone to two potential problems. First, it overweighs outliers in lending patterns. A county might be highly relevant for a bank for all years except one or vice-versa. Second, mortgages represent arguably long-term exposures, which is also the reason why they are an exposure risk for flooding far out in the future. Hence, to address the two aspects, columns (6) and (7) use three-year rolling averages as weights. Across all specifications, the result is negative and statistically significant with a coefficient β_1 between -0.18 and -0.13 and t-statistics ranging from -3.3 to -2.1. These results echo the coefficient in the baseline regression of column (1). The

Important is that the different measures all capture a very similar exposure. The last column of Table 5 reports a placebo test, where the exposure measure is intended to capture a different channel. Instead of dividing the number of retained mortgages in a county by the total retained mortgages by a given bank, a bank's retained mortgages are divided by the total aggregate number of originated mortgages in that county (across all lenders). The exposure measure captures the county-level market concentration from the perspective of a single bank. The prediction is that the result from this regression should be insignificant and different from the other results. The coefficient on the exposure measure is positive and insignificant suggesting that a different channel is at work in this scenario.

All in all, the results suggest that bank stocks under-react to the risk of floods. The literature on climate risk has brought forth several different explanations, which are analyzed next.

4.2. Heterogeneity of Effects

As seen in Section 3.3, bank heterogeneity plays an important role in the relation between bank performance and flood realizations.

To examine the importance of the heterogeneity for the return predictability, Table 6 presents separate estimates of equation 7 for banks with a high share of mortgage lending (High) compared to banks with a lower share of mortgage lending (Low), and small banks compared to large banks. The partitioning is based on the median of the mortgage lending share and size, respectively.

Panel A of Table 6 reports the estimates from regressing the excess return on the *Flood Risk Exposure* for the mortgage share-sorted banks. Columns (1) and (2) report the coefficients for the subsamples, while the result in column (3) includes an interaction term between *Flood Risk Exposure* and an indicator variable if the bank has a large share of mortgages. The coefficients on *Flood Damage Exposure* are negative for the two subsamples, but only significantly for the subsample of banks specialized in mortgage lending. The point estimate in column (1) is almost double the magnitude of the point estimate in column (2). For the sample of banks specialized in mortgage lending, a 1-standard-deviation increase in the exposure reduces the excess return by -25 bps, or -3% annualized. However, the interaction in column (3) is not statistically significant either, suggesting that the difference between the two coefficients in columns (1) and (2) is not large enough to warrant largely different conclusions. If anything, the finding is consistent with banks specializing in mortgage lending being more exposed than other banks.

[Table 6 about here]

More interestingly, Panel B of Table 6 reports the estimates for the size-sorted samples. Only the point estimate on *Flood Risk Exposure* for the sample of small banks is negative and statistically significant (with a t-statistics of -3.8). The point estimate is equal to -30 bps, which translates into 3.7% annualized. The coefficient for the sample of larger banks is even positive, albeit insignificant. This suggests that the result does not appear to be due to a lack of statistical power, as the coefficients are not only statistically insignificant but also of a different sign. The difference between the two coefficients is also statistically significant as shown by the interaction term in the last column. Several hypotheses might explain the discrepancy between small and large banks. First, large firms are typically more visible. They attract more scrutiny from investors and analysts but are often also required to disclose more information. This is especially true in the banking industry, where large banks have always been treated differently, but even more so since the Great Recession. The positive (insignificant) coefficient for the sample of large banks is evidence that investors are better able to price the risk exposure to flooding. The opacity and lack of disclosure of smaller banks make the pricing of risk more difficult.

The results suggest that heterogeneity in banks is an important driver of the baseline result. The negative predictability of flood risk exposure is concentrated in small banks, and banks with a higher share of mortgage lending, although to a lesser extent than size. Smaller banks are typically less diversified and therefore more exposed to regional shocks. One worry is that the flood risk exposure picks up other regional factors that drive the negative predictability.

4.3. Portfolio-Level Analysis

Having established that banks with high exposure to flood risk underperform in the cross-section of bank stocks, I now use portfolio sorts to examine the return difference of banks with high and low exposure. Banks are sorterd in quartiles according to their flood risk exposure. Then, the value-weighted returns of the four portfolios are computed. I estimate following time-series regressions:

$$r_{it} - r_t^f = \alpha_i + \boldsymbol{\beta_i}'\mathbf{F}_t + \epsilon_{it}, \tag{8}$$

where r_{it} is the monthly return on the i$^{\text{th}}$ flood exposure sorted portfolio. The vector $\boldsymbol{F}$ includes six factors: the four factors from Carhart (1997) (the market (Mkt-r^f), small minus big (SMB), high minus low (HML) and momentum (Mom)); and two bond factors from Gandhi and Lustig (2015), ltg that is the excess return on an index of long-term U.S. Treasury bonds and crd, the excess return on an index of investment-grade high-quality corporate bonds.

[Table 7 about here]

Table 7 reports the estimates from equation 8. Panel A presents the results for the full sample running from 2004 to 2020. Columns (1) to (4) report the results for the four portfolios. The intercept decreases from 0.38% in poto 0.05%, albeit not monotonically. Column (5) reports the results from running the time-series regression for a portfolio that goes short portfolio 1 and long portfolio 5, i.e., it goes short the portfolio with the lowest exposure and long the portfolio with the highest exposure. The intercept on the High-Low portfolio has a value of -0.43 and a t-statistic of -3.3. The intercept translates into a 43 bps monthly loss, or -5% annualized.

As in the previous section, small and large banks are analyzed separately. Panel B of Table 7 reports the intercepts of the four flood risk exposure-sorted portfolio for the sample of small banks. The intercepts decrease monotonically as we move from portfolio 1 (in column (1)) to portfolio 4 (in column (4)). The difference between the intercepts in portfolios 5 and 1 is equal to -0.77 and statistically significant at the 1% level. The High-Low portfolio losses 9.6% per month in annualized terms. Finally, Panel C of Table

7 reports the intercepts for the sample of large banks. No discernible pattern in alphas is observed in this last panel. In line with the previous findings, this suggests that the potential role of flood risk exposure is restricted to smaller banks.

4.4. Flood Risk Factor

Next, motivated by the climate factor in Pástor et al. (2021), I use banks' flood risk exposure to construct a flood risk factor. Banks are independently assigned into two portfolios. The first portfolio consists of banks with an individual flood risk exposure below the overall 25$^{\text{th}}$ percentile. The second portfolio collects banks with a flood risk exposure above the 75$^{\text{th}}$ percentile. The flood risk factor is then obtained by going long the banks in the second portfolio (high exposure) and short the bank stocks in the first portfolio (low exposure).

[Figure 6 about here]

Figure 6 plots the cumulative returns of the two exposure-weighted portfolios and the high-low portfolio for the full sample of banks and months. The dotted blue line (squares) reports the cumulative return of the high exposure portfolio, while the dashed blue (triangle) line plots the cumulative return of the low exposure portfolio. Both portfolios increase over the sample running from 2004 to 2020, but the low-exposure portfolio grows much faster. This is seen in the cumulative return of the high-low portfolio plotted in solid orange (circles). Except for the period around the financial crisis in 2007-2009, the high-low portfolio losses systematically. It ends over 50% lower in 2020.

The monthly return difference, denoted by *Flood Factor*, averages -24 bps per month, as reported in the first column of Panel A of Table 8. This consistent under-performance of the flood factor cannot be fully explained by exposure to other factors prominent in the asset pricing literature. Column (2) includes the market factor. Columns (3) and (4) add the three Fama and French (1993) and Carhart (1997) four factors. In all cases, the flood factor's alpha (regression intercept) has a very similar magnitude ranging from -0.2 to -0.24 with t-statistics between -1.60 and -1.86. The flood factor's exposures to SMB, HML, and Mom indicate that it is slightly leaning toward larger stocks, growth stocks, and recent winners, although none of the coefficients are statistically significant.

[Table 8 about here]

As size heterogeneity played an important role in the previous analysis, Panel B of Table 8 constructs the flood factor without the largest 25% of banks. The table only reports the intercepts, but as previously, column (1) includes no control, column (2) adds the market factor, column (3) controls for the three Fama and French (1993) return factors, while column (4) reports the results with the Carhart (1997) four factors. The magnitude of the alpha jumps to -0.56 or -56 bps per month and remains unchanged even when controlling for the other asset pricing factors. And even though the sample includes fewer banks, the statistical significance also increases with t-statistics ranging from -2.1 to -2.5.

Panel C of Table 8 constructs the flood factor, but only with the largest 25% of banks. The monthly return difference flips sign and averages 1 bps but is not statistically significant as reported in column (1). Sequentially including the different additional factors does not change the magnitude nor the significance by much. The finding underlines the hypothesis that investors are able to better price the exposure for larger banks. The return differences for the sample of large banks are consistent with the other findings based on bank heterogeneity.

Along the same lines, Figure 7 plots the cumulative return of the flood factor for the two size-sorted subsamples using exposure-weighted and equal-weighted cumulative returns. The time series for the sample of small banks are shown in orange. The solid line plots the exposure-weighted cumulative return of the flood factor based on the sample of small banks. The portfolio loses over 60% over the sample (or almost 100% if we consider the covid-related drop in 2020). The pattern is very similar for the equal-weighted portfolio (dotted line) but less steep. For both portfolios, the cumulative return decreases almost monotonically until 2016 when it increases slightly for a few quarters before decreasing again in 2019. The two return series suggest a steady underperformance of the high-exposure banks that is not solely driven by an outlier. The reason for the flatter curve around 2016 could be due to changes in the regulatory environment. The cumulative return of the flood factor based on the 25% largest banks is flat over the sample. The equal-weighted and exposure-weighted cumulative returns increase until 2016 when they reach around 15%. The equal-weighted cumulative return remains at this level, while the exposure-weighted cumulative return decreases back to 0%.

[Figure 7 about here]

4.5. Time-Series Variation of the Flood Risk Factor

To complement Table 11, I estimate how much of the return variation of the flood factor is attributed to flood damages:

$$r_t^{FF} = \alpha + \beta \mathit{Flood\ Damages}_t + \epsilon_t, \tag{9}$$

where r_t^{FF} is the monthly return on the flood factor and *Flood Damages* is either the monthly amount of flood damages, the monthly average across all counties, or an indicator variable for large disasters.

[Table 9 about here]

The estimates for the full sample of banks are reported in Panel A of Table 9. Again, three different measures of damage exposure are used. Column (1) uses flood-related damages, column (2) is again an indicator variable equal to 1 if the damages are in the top decile, and column (3) aggregates costs across all types of disasters. The variables in columns (1) and (3) are defined as changes because the damages are now summed up across the U.S. every month. The flood realization enters with the expected negative sign in all three specifications. It is also significant in columns (1) and (3). The R-squared is low in all three regressions.

The key measure of interest is the estimate of the regression intercept. The magnitude of the estimate is still in line with the previous findings, but it is not statistically significant anymore, which might be some more, albeit weak, evidence that the flood risk exposure measures disaster realizations to some extent. However, if we only focus on the sample of smaller banks, this finding vanishes again.

Panel B of Table 9 presents the results for small banks. While the sign on flood realization is still negative in all specifications, it is never significant. And the estimated intercept remains negative and significant as in the results from the previous sections.

5. Economic Mechanism

Standard asset pricing models predict that riskier assets have higher expected returns than safer assets, due to investors' risk compensation needs. In the context of this analysis, this implies that stocks of banks with a higher flood risk exposure trade at a positive risk premium. Using realized returns, the previous section demonstrated that flood risk-exposed banks traded at a significant negative flood risk premium. This wedge between expected returns and realized returns can be driven by several causes.

First, exposed assets can have lower realized returns when the underlying risk materializes, i.e. the economy is shocked by a flood disaster. To test this, I additionally control for periods of flood disasters. Second, as knowledge about and attention to climate change increases, investors' preference for safer unexposed assets increases, which leads to a shift in asset demand. The shift drives up prices of safer assets, while simultaneously decreasing the price of exposed assets (Pástor et al., 2022). This is tested by analyzing whether periods of high attention to climate change explain the overall underperformance of flood risk exposed banks.

5.1. Exposure to Disaster Realizations

The bank-level flood risk exposure captures underlying differences in flood probabilities of the different regions in the United States. Therefore it is likely correlated with past and future flood disasters. A region prone to floods in the future has likely incurred floods in the past. This implies that the flood risk exposure measure might simply be picking up these negative (unanticipated) flood shocks. This in turn could explain the negative coefficient on the flood risk exposure uncovered in the previous section.

To rule out that the negative flood risk premium is driven by periods of disasters, I repeat the cross-sectional analysis by removing observations that fall within a month of a flood disaster. The assumption to test is whether flood disasters are the main driver behind the negative coefficient on flood risk exposure. Table 10 reports the results for four subsamples of the data. First, major disasters are removed from the sample. In column (1) of Table 10, the months around Hurricane Katrina are omitted. Specifically, the months from August to October of 2005 are deleted. Column (2) removes other major storms (e.g., Hurricane Sandy and Hurricane Harvey). Second, the sample is restricted to banks unaffected by any disasters. Column (3) restricts the sample to bank-months with zero exposure to flood disasters, that is their damage exposure used in Section 3 is 0, and column (4) reduces the sample further by confining it to banks with high exposure to flood risk and simultaneously zero damages from floods. Panel A reports the results for the full sample of banks. Panel B is restricted to small banks. And Panel C includes large banks.

[Table 10 about here]

As previously, the negative coefficient on the flood risk exposure remains significant and negative for the full sample and the sample of small banks. Further, magnitudes are almost unchanged. The only insignificant coefficient is in column (4), the most restricted sample, but the point estimates are identical suggesting that the power of the small sample might be an issue in the estimation. The underperformance of flood risk exposed banks cannot be attributed to flood disasters. Exposed banks trade at a discount even in samples without any major disasters.

An alternative approach is to explicitly control for disaster shocks. So, using the estimates for property damages from floods, I control for current disasters by including *Damage Exposure* from equation 2 to the regression framework. Formally, following regression is estimated:

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 Flood\ Risk\ Exposure_{bt} + \beta_2 Flood\ Damages_{bt} \\ &+ \beta_3 Flood\ Risk\ Exposure_{bt} Flood\ Damages_{bt} \\ &+ \beta_4 log(Assets)_{bt} + \beta_5 log(BE/ME)_{bt} \\ &+ \beta_6 Leverage_{bt} + \beta_7 r_{bt-1} + \epsilon_{bt}. \end{aligned} \tag{10}$$

Additionally, the regression includes the interaction term between the disaster realization measure and the exposure to risk, which captures offsetting forces separately.

[Table 11 about here]

Table 11 reports the estimates from equation 10 for three different measures of exposure to flood damages. The damage measure used in columns (1) and (2) is based on the level of property damages from floods and has been aggregated using a bank's mortgage lending. The original measure is in dollar value but has been standardized to simplify the interpretation. Column (3) reports the result using the indicator variable *High Damage* that takes a value of 1 if the bank-level *Damage Exposure* is in the top decile. Finally, the measure in column (4) is the unweighted sum of all damages in a month. It is therefore constant across all banks in a given month.

Panel A of Table 11 reports the estimates for the full sample of banks. The coefficient on the flood risk exposure remains negative and significant. Additionally, the magnitude is almost unchanged. Therefore exposed banks still underperform. If the underperformance was due to disaster shocks, the sign on the flood risk exposure should have flipped. That the sign remains negative implies that disaster exposure cannot explain the poor performance. Nevertheless, the coefficient on the flood damage exposure is also negative and significant in all specifications, which is in line with the hypothesis that floods negatively affect bank performance. Except for column (3), the interaction between the two exposure measures is not statistically significant. The compounding effect of high flood risk exposure and high damage exposure in column (3) mutes the effect as measured by the interacted term, which would be in line with the explanation that past disasters drive performance. The effect is however isolated to one regression. All in all, these results suggest that the current disaster is not the only or main driver of the results in the full sample of banks.

This finding is echoed when focusing on the subsample of small banks. The estimates are reported in Panel B of Table 11. As previously, the magnitude and significance of the regression slopes for flood risk exposure are unchanged. A one-standard-deviation increase in exposure is associated with a 20 bps lower monthly excess return. The coefficients of the three disaster variables are also negative and significant in most cases.

Finally, Panel C of Table 11 reports the estimates for the sample of large banks. Interestingly, the coefficients on the flood risk exposure are positive, albeit not significant. However, this suggests that larger banks are priced differently than smaller banks with respect to flood risk. However, exposure to disaster is associated with lower realized returns. Thus, it appears that investors price the risk of flooding more adequately for larger banks, but potentially not to the full extent, as this would imply a positive risk premium.

The results suggest that exposure to flood realizations for the sample of small banks cannot explain the negative coefficient on the exposure to flood risk. However, the exposure to disasters has explanatory power itself, as seen by the significant coefficients. Large banks experience no underperformance with respect to the flood risk exposure, while exposure to disasters also commands poor performance. The divergence between the size-sorted samples suggests that investors are able to price the exposure to flood risk more precisely for large banks. As discussed earlier, large and small banks differ in several characteristics and disclosure requirements that could help explain this finding.

5.2. Reaction to Climate Change Concerns

To the extent that we would expect higher returns of stocks with high exposure to flood risk as compensation for that risk, we should find that stocks of high flood risk banks perform significantly worse than unexposed stocks in periods of increased attention toward, and concerns about climate change risk. This conjecture is tested by examining the performance of bank stocks when explicitly controlling for attention to climate change and natural disasters. An alternative story with the same implications is that climate change concern is a relatively new phenomenon as pointed out by Pástor et al. (2021). Therefore, it is likely affecting returns. The last one to two decades can be seen as a transition period in which investors' preferences and demands for assets that allow hedging climate risks have changed considerably. So, while the expected return of a bank highly exposed to flood risk should be positive compared to a bank without exposure, the changing nature of climate concerns leads to a lower realized performance of the exposed bank. Or in other words, investors may move away from assets highly exposed to future risk as news about climate change becomes public. This leads exposed stocks to underperform during this transition period.

Both conjectures are tested using different measures of attention to climate change. First, I download frequency data from Google Search Volume Index (SVI) for the topic of climate change and floods more specifically, which has been shown to be a reliable proxy of investor attention (e.g., Da et al., 2011). This data is a proxy for widespread awareness about climate change and its potential effects. It is available since 2004 at a monthly frequency.

Second, I use the monthly version of the Media Climate Change Concerns (MCCC) index based on climate change-related newspaper articles introduced by Ardia et al. (2022).[14] The index is available from January 2003 to June 2018 and is constructed from ten newspapers and two newswires. The rationale for using this measure is that the media have been shown to be an important driver of public awareness. The advantage of the MCCC index is that it captures the negative sentiment in the news articles as opposed to a measure introduced by Engle et al. (2020). Following Ardia et al. (2022), I use a measure of unexpected media climate change concerns (UMC) that is defined as the prediction errors from an AR(1) regression model calibrated on the MCCC index. An additional benefit of their data is that an index is available for an array of different components. While the focus is on the aggregated measure, the results for an index focused on flood-related concerns, climate summits, and global warming are shown separately. This allows disentangling concerns about physical risks from transition risks.

The estimates from these regressions are reported in Table 12. All regressions include a large set of bank controls (log(assets), log(book-to-market), Tier 1 leverage ratio, and the previous month's return) as well as economic variables such as log(GDP), log(PCPI), log(PCE), the unemployment rate, and the change in the VIX. The key measure of interest is ΔCC, the change in climate change concern. In columns (1) and (2), ΔCC uses search data for the topics 'Climate Change' and 'Floods' from Google (SVI), while in columns (3) to (5) it is based on the MCCC index data from Ardia et al. (2022). The measures have been standardized to ease comparison across regressions.

Panel A of Table 12 reports the results for the full sample of banks. The measure of climate change concern enters negatively in all specifications and is significant with t-statistics between -3.2 and -11.9 in all but one regression. However, the coefficient on *Flood Risk Exposure* remains significant and negative, suggesting that it is not just capturing changes in investor preferences. Additionally, the interaction term provides evidence that the effect of climate change concern holds for all banks, which suggests that investors might view banks as a bad hedge against climate change-related risks. The findings from the full sample of banks are echoed in the sample of small banks as reported in Panel B of Table 12. The coefficients on *Flood Risk Exposure* are always negative and significant with t-statistics below -3.2. The magnitude on ΔCC for the full sample and the sample of small banks are also very similar for the different measures.

This exercise showed that climate change concerns matter for the performance of bank stocks, but the concerns fail to explain the negative return predictability of flood risk exposure.

[Table 12 about here]

[14]The MCCC index is available for download at `https://sentometrics-research.com`.

6. Robustness

This section examines whether the poor return performance of flood risk exposed banks is driven by other potentially omitted variables.

6.1. Flood Insurance

Flood insurance could be another cause for the return underperformance of flood risk exposed banks. Banks have been shown to increase their lending following major natural disasters because household and firm demand increase for rebuilding purposes (e.g., Cortés and Strahan, 2017; Rehbein and Ongena, 2020). So if all potential losses are covered by insurance, a bank could in theory benefit from a disaster. 3 has shown that this is most likley not the case as bank performance measured by an array of different variables deteriorates following a flood disaster. Nevertheless, this section tests the potential bias of the flood insurance market by explicitly controlling for it.

In the United States, the standard home insurance contract covers some natural disasters such as fire, but it explicitly excludes floods (Oh et al., 2022).[15] Flood insurance has to be taken separately and is provided federally by the National Flood Insurance Program (NFIP). Flood insurance is technically required by law for most mortgage borrowers in FEMA-designated flood zones. However, there are a couple of important caveats. Federal flood insurance only covers mortgages up to $250,000 in flood damage, and virtually no private insurers are available for the remaining coverage. Further, insurance contracts are short-dated with yearly renewals, leading to many borrowers dropping out. And flood insurance is only mandatory in officially designated flood zones, leaving many properties at risk. The NFIP has, on average, 5 million active contracts compared to 15 to 36 million homes that are estimated to be exposed to disaster risk.[16] An additional reason for the diverging numbers between the insured and at-risk homes is that climate change has led to significant changes in the underlying risk and increased risk-sensitive regions. So keeping up with these changing patterns is important if insurance coverage should match actual risks. While FEMA is mandated to update its maps at a five-year interval, most of them are older. This results in a mismatch of insured and exposed homes.

To test the effect of flood insurance formally, I use the flood insurance policy data from NFIP published by FEMA. The data is available in two separate files. The first file includes information on active policies and is available from 2009 to 2022. It includes information such as the coverage and premium of individual policies. On average, the data includes around 4 million active policies compared to the estimated 15 million homes

[15] The most widespread home insurance contract called HO3 accounts for 95% of all sold contracts.

[16] Flavelle et al. (2020) estimates 15 million properties at risk from a 100-year flood, while RealtyTrac (2016) estimates 36 million homes at risk from natural disasters.

at high risk of flooding. The total insured amount is $1 trillion, with building coverage of roughly $750 billion, while around $250 billion in content is covered. The number of active policies has slightly decreased in recent years. As expected, coastal regions in the Gulf have the highest number of active policies. The second file from the NFIP includes information on policy claims. And similarly to before, claims are concentrated around the Gulf.

Columns (1) and (2) of Table 13 report the estimates of the cross-sectional regressions that include the variables for flood insurance penetration. In column (1), *Flood Policies* is the retained mortgage-weighted average of the number of active flood policies from the NFIP, which reduces the potential fallout from future floods for exposed banks. The control in column (2) is based on policy payouts for insured buildings and captures flood realizations. Through the three samples of banks, controlling for flood insurance does not alter the magnitude nor significance of the estimate on the flood risk exposure. Small flood risk exposed banks underperform by about 30 bps per month. Exposure to more or fewer flood insurance policies does not seem to have any predictive power, which alleviates concerns that differences in flood insurance take-up might be driving the negative risk premium. Flood claims load significantly negatively. However, this effect is reassuring, because flood claims are also highly correlated with flood disasters and the intensity of a disaster.

The current evidence suggests that banks remain exposed to floods, even if banks partly manage flood risk when originating mortgages and some borrowers are insured against floods.

[Table 13 about here]

6.2. Mortgage Delinquencies

All explanatory variables used in the analysis are based on a bank's mortgage lending activity. One additional worry is that the findings are not driven by the flood damage or risk exposure component, but by the mortgage part of the measures. The variables could simply be picking up the differing performance of the local real estate market.

Columns (3) and (4) of Table 13 test this conjecture by controlling for banks' exposure to foreclosures or defaults. Again, through the different samples, the baseline results persist: in the full sample and for small banks, flood risk exposed banks underperform with a monthly flood discount of 20 to 30 bps. Defaults load negatively in the three samples, suggesting that poor real estate performance is associated with lower future returns as hypothesized.

6.3. Regional shocks

To rule out the possibility of other shocks, I control for additional regional measures. The estimates are collected in Table 14.

Table 14 focuses on state-level controls. Column (1) includes state-level macroeconomic variables, such as $log(GDP)$, inflation, income per capita, and unemployment rate. The state-level variables are aggregated at the bank level using the same method as for the county-level flood probabilities presented in Section 2.5. Each state-level measure is weighted by the dollar amount of mortgages retained by a bank in that given state. Column (2) includes 50 state indicator variables. For a given bank, a state indicator takes on the value of 1 if the bank has originated a mortgage in that state. This approach can be viewed as a form of manually including state-fixed effects. Column (3) interacts the state dummies with year dummies. Finally, column (4) includes HQ-state-fixed effects.

Across the four specifications, the coefficient on the *Flood Risk Exposure* is negative, ranging from -0.24 to -0.12, suggesting that the finding is not driven by unobserved regional characteristics.

The results from Table 14 are evidence that the baseline finding is not driven by unobserved regional characteristics captured by the *Flood Risk Exposure*.

[Table 14 about here]

7. Conclusion

Climate change-related disasters are projected to increase and become considerably more extreme over our lifetime. Policymakers are increasingly worried that these disasters could negatively affect banks and financial stability (e.g., Lagarde, 2021).

Focusing on flood disasters, in this paper, I provide evidence that the residential real estate market transmits flood shocks to the banking sector. The first contribution is constructing a bank-level flood risk exposure measure that combines up-to-date flood risk maps with bank mortgage lending data. Previous literature has focused on the physical location of banks to measure their exposure to shocks, but in this paper, I argue that the balance sheet composition matters. I show that banks underperform following a flood disaster. While the initial shock is not large in magnitude, the effects are long-lasting and affect various performance measures. Not only do loan charge-offs increase, but profitability decreases for up three quarters. Furthermore, I find that disasters significantly negatively impact household delinquencies and foreclosures, which directly spill over to bank operations. Together with the projected increase in severity and frequency of flood disasters, this suggests that the negative impact of floods will worsen.

The second contribution is to assess whether these risks are reflected in bank stock prices. I address this question by undertaking a cross-sectional stock returns analysis, with bank-level flood risk exposure as the key bank characteristic. I uncover the puzzling finding that flood risk exposure negatively affects bank stock returns. The negative predictability only holds for smaller banks but is sizeable for this group. On average, a one-standard-deviation increase in exposure results in a 3.6 percentage point lower annualized excess return. Consistent with the findings in Faccini et al. (2021), Hong et al. (2019), and Manela and Moreira (2017), the results suggest that physical risk from flooding is not fully priced in the cross-section of bank stock returns. A portfolio that goes long banks with a high flood exposure and short banks with low exposure loses around 20 bps per month in the full sample, or 55 bps when only considering small banks. The return on the portfolio cannot be explained by standard factors used in the asset pricing literature. Taken together with the first set of results, this suggests that while large and small banks are affected by flood realizations, only the stock returns of smaller banks react to the risk.

I shed light on how the flood risk exposure negatively relates to the bank stock returns. First, past flood disasters cannot fully explain the negative predictability. While flood disasters lead to weaker stock performance, the negative relation of flood risk exposure remains. Second, the effect is not driven by investor attention or knowledge about climate change. Using the MCCC index from Ardia et al. (2022) and search data from Google, I find that climate change concern has negative predictability for bank stock returns regardless of the bank's exposure to flood risk. Still, the negative predictability of flood risk exposure persists.

The results suggest that banks are negatively affected by flood realizations but that investors do not directly or entirely pay attention to physical risks from flooding but are more worried about climate policy risks in line with findings from Ardia et al. (2022).The negative return predictability of the flood risk exposure for smaller banks suggests that investors withdraw from this segment of the market. However, both types of banks are affected by disaster realizations. Therefore, the results may warrant the views expressed by a number of policymakers that exposure to physical risks from climate change should be monitored.

References

Acharya, Viral V, Tim Johnson, Suresh Sundaresan, and Tuomas Tomunen, 2022, Is physical climate risk priced? Evidence from the regional variation in exposure to heat stress, Working Paper.

Ardia, David, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht, 2022, Climate change concerns and the performance of green versus brown stocks, Working Paper.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? Only if you believe in it, *The Review of Financial Studies* 33, 1256–1295.

Barth, James R., Yanfei Sun, and Shen Zhang, 2019, Banks and natural disasters, Working Paper.

Bernstein, Asaf, Matthew T. Gustafson, and Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 253–272.

Bessler, Wolfgang, and Philipp Kurmann, 2014, Bank risk factors and changing risk exposures: Capital market evidence before and during the financial crisis, *Journal of Financial Stability* 151–166.

Blickle, Kristian, Sarah Ngo Hamerling, and Donald P. Morgan, 2021, How bad are weather disasters for banks?, Federal Reserve Bank of New York Staff Reports 990.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, forthcoming, Global pricing of carbon-transition risk, *Journal of Finance* .

Bongaerts, Dion, Francesco Mazzola, and Wolf Wagner, 2021, Fire sale risk and credit, *SSRN Electronic Journal* .

Bos, Jaap W. B., Runliang Li, and Mark W. J. L. Sanders, 2022, Hazardous lending: The impact of natural disasters on bank asset portfolio, *Economic Modelling* 108, 105760.

Brainard, Lael, 2021, Speech by Governor Brainard on building climate scenario analysis on the foundations of economic research.

Brown, James R., Matthew T. Gustafson, and Ivan T. Ivanov, 2021, Weathering cash flow shocks, *The Journal of Finance* 76, 1731–1772.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Carney, Mark, 2015, Breaking the tragedy of the horizon - climate change and financial stability, Speech, Bank of England.

Casu, Barbara, Andrew Clare, Anna Sarkisyan, and Stephen Thomas, 2013, Securitization and bank performance, *Journal of Money, Credit and Banking* 45, 1617–1658.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *The Review of Financial Studies* 33, 1112–1145.

Cortés, Kristle Romero, and Philip E. Strahan, 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* 125, 182–199.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *The Journal of Finance* 66, 1461–1499.

Davenport, Frances V., Marshall Burke, and Noah S. Diffenbaugh, 2021, Contribution of historical precipitation change to US flood damages, *Proceedings of the National Academy of Sciences* 118, e2017524118.

Doerr, Sebastian, and Philipp Schaz, 2021, Geographic diversification and bank lending during crises, *Journal of Financial Economics* 140, 768–788.

Duan, Tinghua, Frank Weikai Li, and Quan Wen, 2021, Is carbon risk priced in the cross section of corporate bond returns?, Working Paper.

Duguid, Kate, and Ally Levine, 2020, From New York to Houston, flood risk for real estate hubs ramps up, *Reuters* .

ECB, 2019, Financial Stability Review, May 2019, Technical report, European Central Bank.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *The Review of Financial Studies* 33, 1184–1216.

Faccini, Renato, Rastin Matin, and George Skiadopoulos, 2021, Dissecting climate risks: Are they reflected in stock prices?, Working Paper.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Favara, Giovanni, and Mariassunta Giannetti, 2017, Forced asset sales and the concentration of outstanding debt: Evidence from the mortgage market, *The Journal of Finance* 72, 1081–1118.

First Street Foundation, 2021, The cost of climate: America's growing flood risk, Technical report.

Flavelle, Christopher, Denise Lu, Veronica Penney, Nadja Popovich, and John Schwartz, 2020, New data reveals hidden flood risk across america, *The New York Times* 7.

Gandhi, Priyank, and Hanno Lustig, 2015, Size anomalies in U.S. bank stock returns, *The Journal of Finance* 70, 733–768.

Garbarino, Nicola, and Benjamin Guin, 2021, High water, no marks? Biased lending after extreme weather, *Journal of Financial Stability* 54, 100874.

Gibson, Matthew, and Jamie T Mullins, 2020, Climate risk and beliefs in New York floodplains, *Journal of the Association of Environmental and Resource Economists* 7, 1069–1111.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *The Review of Financial Studies* 34, 3527–3571.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2019, Climate risks and market efficiency, *Journal of Econometrics* 208, 265–281.

Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou, 2021, The Pollution Premium, Working Paper.

Ilhan, Emirhan, 2021, Sea level rise and portfolio choice, Working Paper.

Intergovernmental Panel on Climate Change, 2015, Climate change 2014: Synthesis report, Technical report.

Ivanov, Ivan T., Marco Macchiavelli, and João A. C. Santos, 2022, Bank lending networks and the propagation of natural disasters, *Financial Management* .

Keys, Benjamin, and Philip Mulder, 2020, Neglected no more: Housing markets, mortgage lending, and sea level rise, National Bureau of Economic Research Working Paper 27930.

Klein, Rudolf F., and Victor K. Chow, 2013, Orthogonalized factors and systematic risk, *The Quarterly Review of Economics and Finance* 175–187.

Koetter, Michael, Felix Noth, and Oliver Rehbein, 2020, Borrowers under water! Rare disasters, regional banks, and recovery lending, *Journal of Financial Intermediation* 43, 100811.

Laeven, Luc, and Ross Levine, 2007, Is there a diversification discount in financial conglomerates?, *Journal of Financial Economics* 85, 331–367.

Lagarde, Christine, 2021, Climate change and central banking, in *ILF Conference on Green Banking and Green Central Banking.*, Keynote Speech.

Manela, Asaf, and Alan Moreira, 2017, News implied volatility and disaster concerns, *Journal of Financial Economics* 123, 137–162.

Meiselman, Ben S., Stefan Nagel, and Amiyatosh Purnanandam, 2020, Judging banks' risk by the profits they report, Working Paper.

Mian, Atif, and Amir Sufi, 2011, House prices, home equity-based borrowing, and the U.S. household leverage crisis, *American Economic Review* 101, 2132–2156.

Murfin, Justin, and Matthew Spiegel, 2020, Is the risk of sea level rise capitalized in residential real estate?, *The Review of Financial Studies* 33, 1217–1255.

National Academies of Sciences, 2016, Attribution of extreme weather events in the context of climate change, The National Academies Press.

National Weather Service New Orleans, 2005, Urgent - Weather Message.

NOAA, National Centers for Environment Information (NCEI), 2022, U.S. billion-dollar weather and climate disasters,, https://www.ncei.noaa.gov/access/billions.

Noth, Felix, and Ulrich Schüwer, 2018, Natural disaster and bank stability: Evidence from the U.S. financial system, SAFE Working Paper.

Oh, Sangmin S, Ishita Sen, and Ana-Maria Tenekedjieva, 2022, Pricing of climate risk insurance: Regulation and cross-subsidies.

Ouazad, Amine, 2020, Coastal flood risk in the mortgage market: Storm surge models' predictions vs. Flood insurance maps, Technical Report arXiv:2006.02977, arXiv.

Ouazad, Amine, and Matthew E Kahn, 2021, Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters, *The Review of Financial Studies* 00, 1–49.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

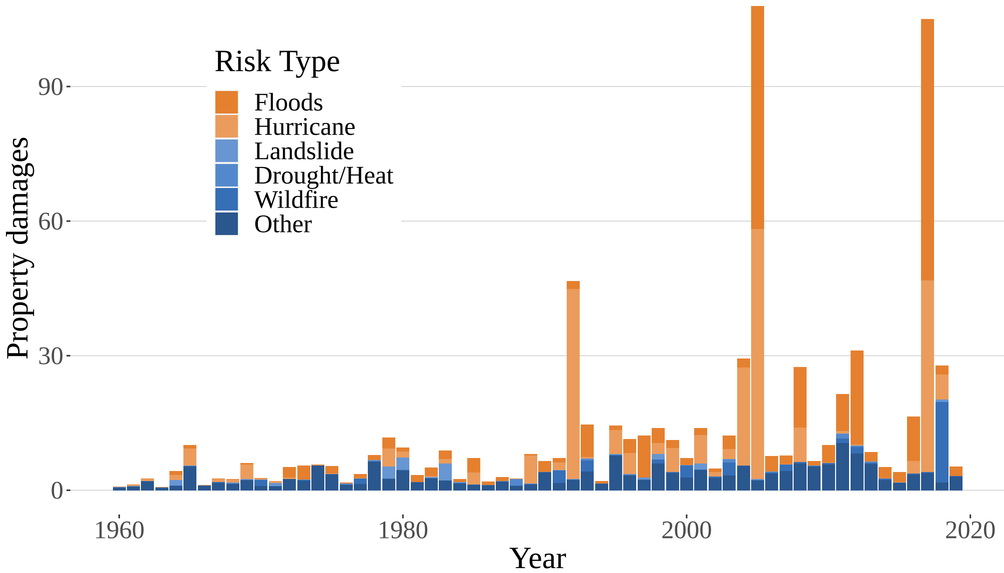
RealtyTrac, 2016, Housing news report .

Rehbein, Oliver, and Steven R. G. Ongena, 2020, Flooded through the back door: The role of bank capital in local shock spillovers, Working Paper.

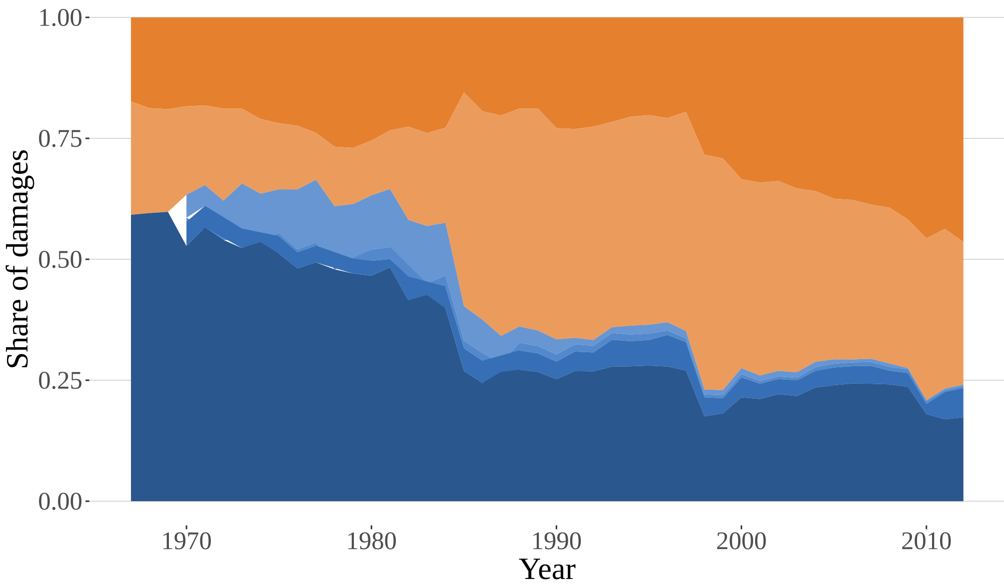
Schüwer, Ulrich, Claudia Lambert, and Felix Noth, 2019, How do banks react to catastrophic events? Evidence from Hurricane Katrina, *Review of Finance* 23, 75–116.

United States Department of Commerce, 2006, Service assessment Hurricane Katrina.

8. Figures



a) Property Damage Estimates



b) Share of Damage Estimates

Figure 1: Property Damages Estimates from Natural Disasters. This figure presents the estimates of property damages from natural disasters in the United States. Panel (a) reports annual sums for the different disaster categories. Panel (b) plots the share of each category to the total damages in a year. Shares are computed with a 10-year rolling window.

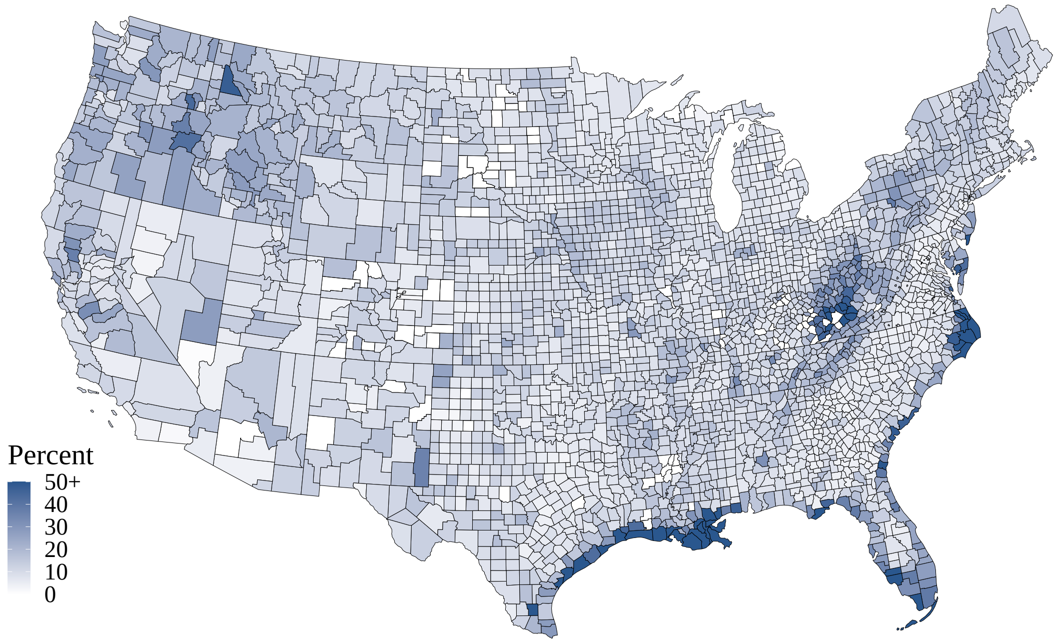
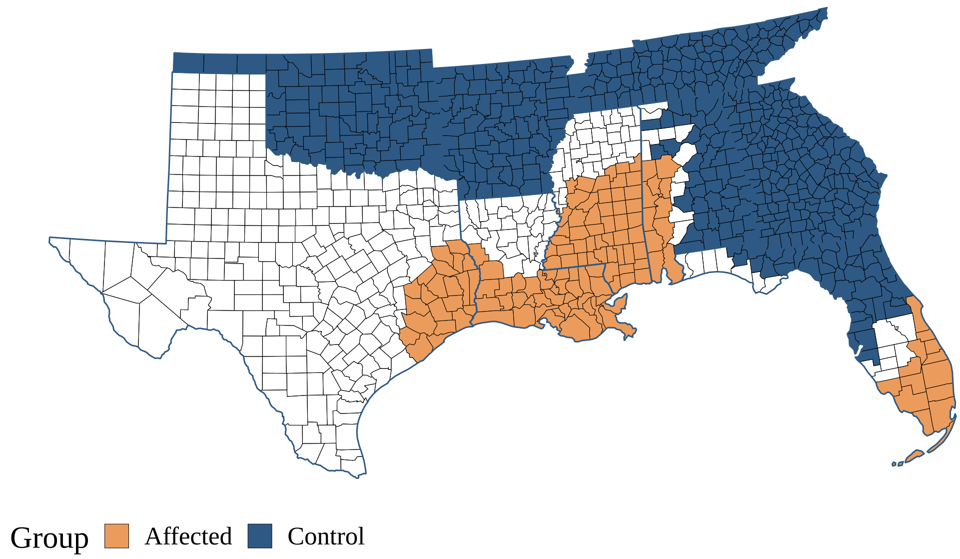
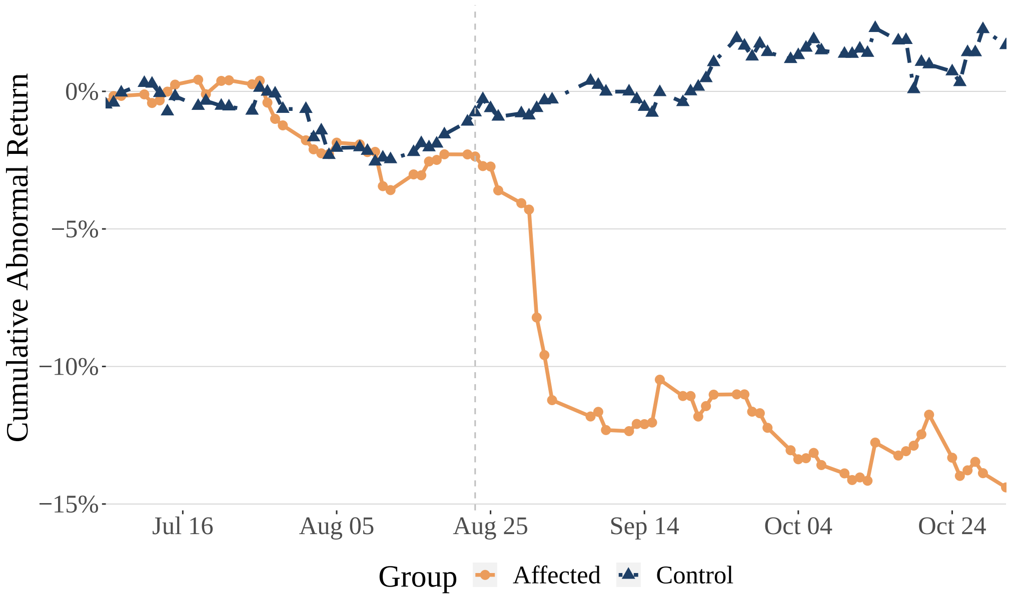


Figure 2: Flood Risk Map. This figure plots the county-level flood risk. The data comes from First Street Foundation and shows the number of properties with a 1% probability of flooding by 2050.

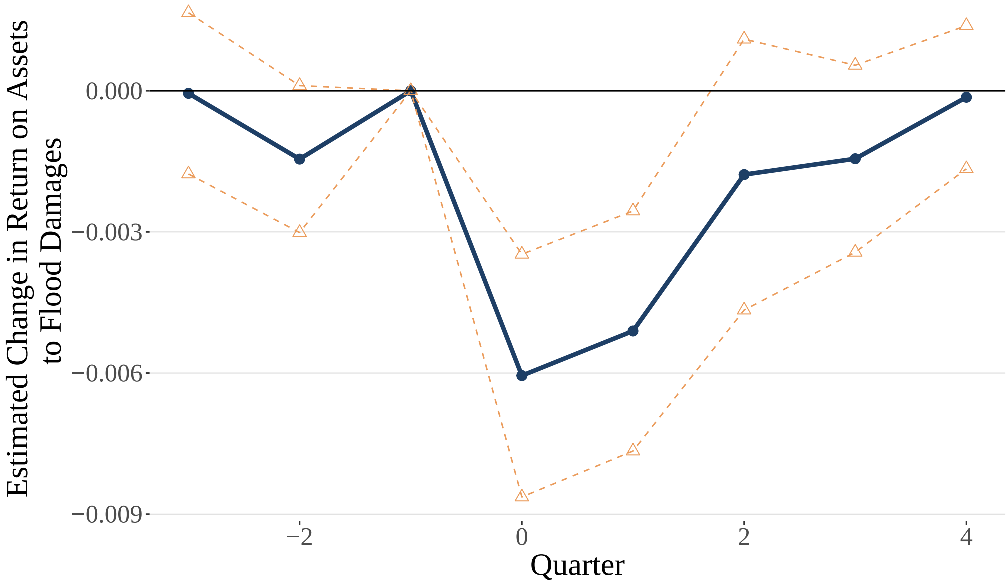


a) Affected Areas

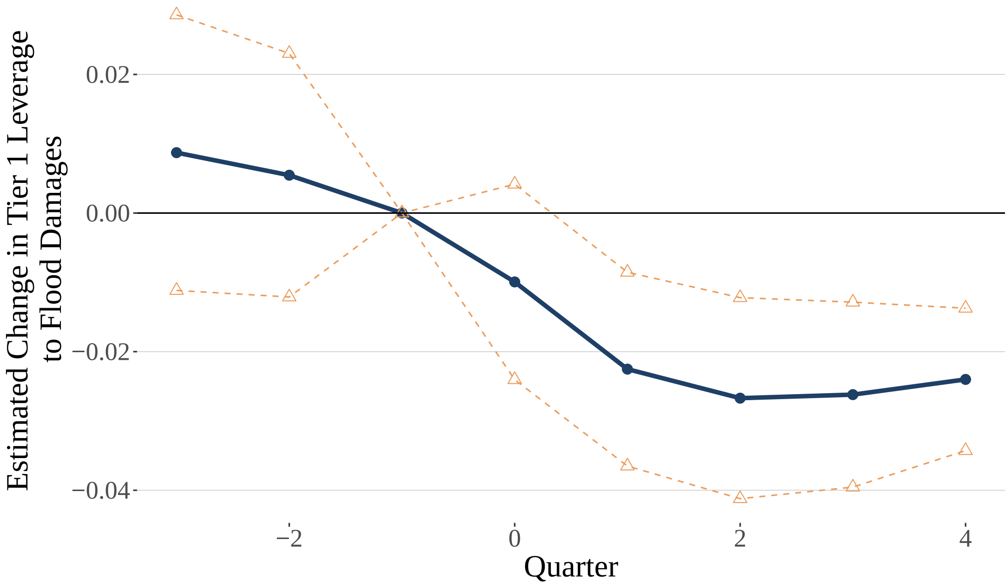


b) Cumulative Abnormal Return

Figure 3: Stock market response to Hurricane Katrina. This figure presents the stock market response to Hurricane Katrina in August 2005. Banks active in counties that received individual disaster relief from the Presidential Declaration Disaster Relief program are defined as treated. The counties are shown in orange in Panel A. Banks active in blue-shaded counties (that received neither individual nor public relief, but are located in the Gulf) are the control group. Panel B reports the cumulative abnormal return of treatment (orange circles) and control group (blue triangles).

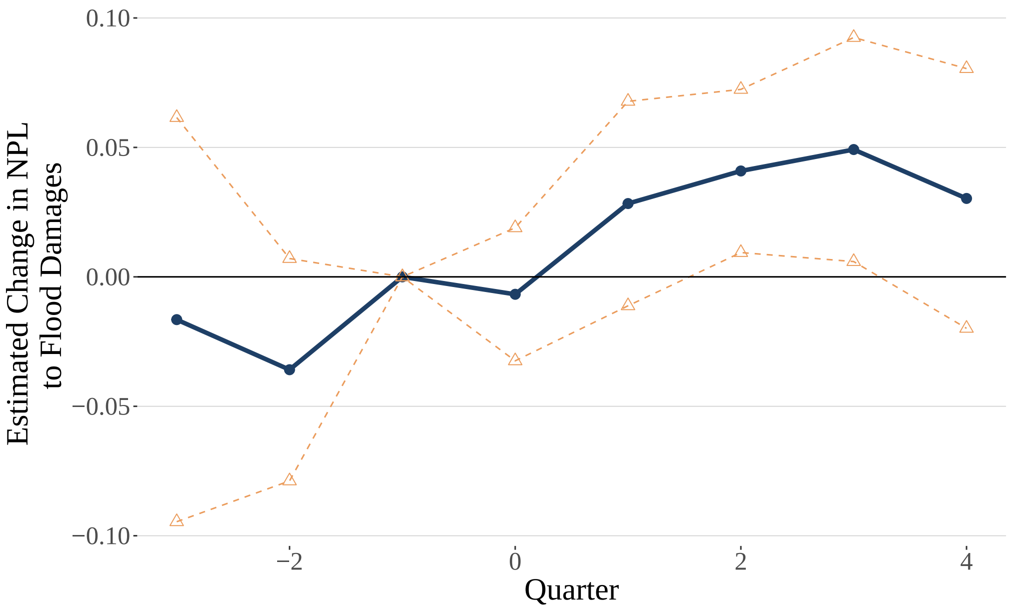


a) Return on Assets

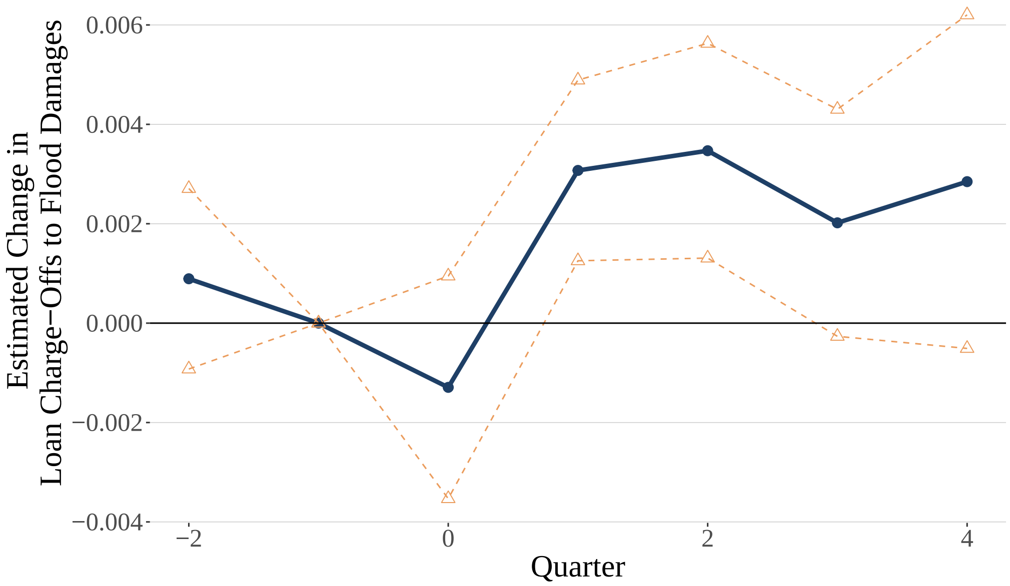


b) Tier 1 Leverage Ratio

Figure 4: Effect of flood disasters on bank performance. This figure presents the relation between bank-level exposure to current flood damages and returns on assets (Panel A) and Tier 1 leverage ratio (Panel B). This figure is estimated by regressing the bank variable in $t+h$ on the exposure to current (t) flood damages, where h runs from -3 to +4 quarters. All regressions are run including *Tier 1 leverage*, *log(assets)*, and the *Mortgage lending ratio*, as well as bank and quarter fixed effects. Standard errors are clustered at the bank level. The solid line presents the point estimates for *Flood Damage Exposure*. The short dashed lines present 97.5% confidence intervals on this estimate.



a) Non-performing Loans



b) Loan Charge-Offs

Figure 5: Effect of flood disasters on loan performance. This figure presents the relation between bank-level exposure to current flood damages and non-performing loans (Panel A) and loan charge-offs (Panel B) for banks with a high share of mortgage lending. This figure is estimated by regressing the bank variable in $t+h$ on the interaction between the exposure to current (t) flood damages and an indicator variable that equals 1 if a bank has a mortgage lending ratio in the top quartile. h runs from -3 to +4 quarters. All regressions are run including *Tier 1 leverage*, *log(assets)*, and the *Mortgage lending ratio*, as well as bank and quarter fixed effects. Standard errors are clustered at the bank level. The solid line presents the point estimates for *Flood Damage Exposure*. The short dashed lines present 95% confidence intervals on this estimate.

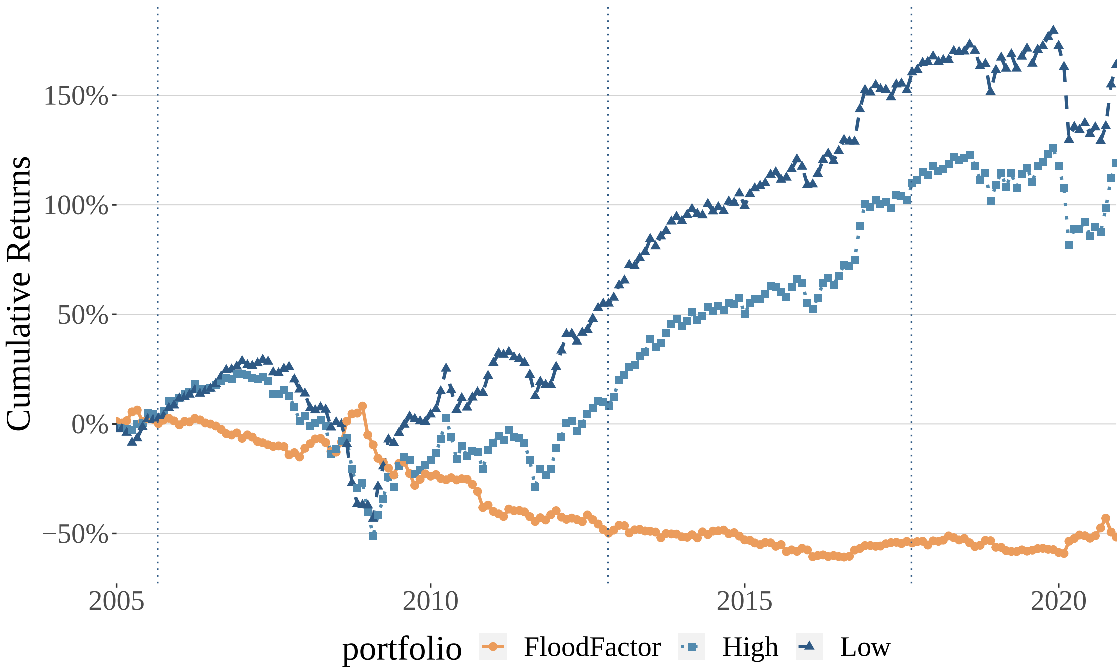


Figure 6: Cumulative Return of the Exposure-Weighted Flood Factor. The solid line plots the cumulative return of the flood factor constructed with banksflood risk exposure. The dotted-blue line (High) plots the cumulative return of the portfolio of banks with high flood exposure, while the dashed blue line (Low) reports the cumulative return of the portfolio of banks with low flood risk exposure.

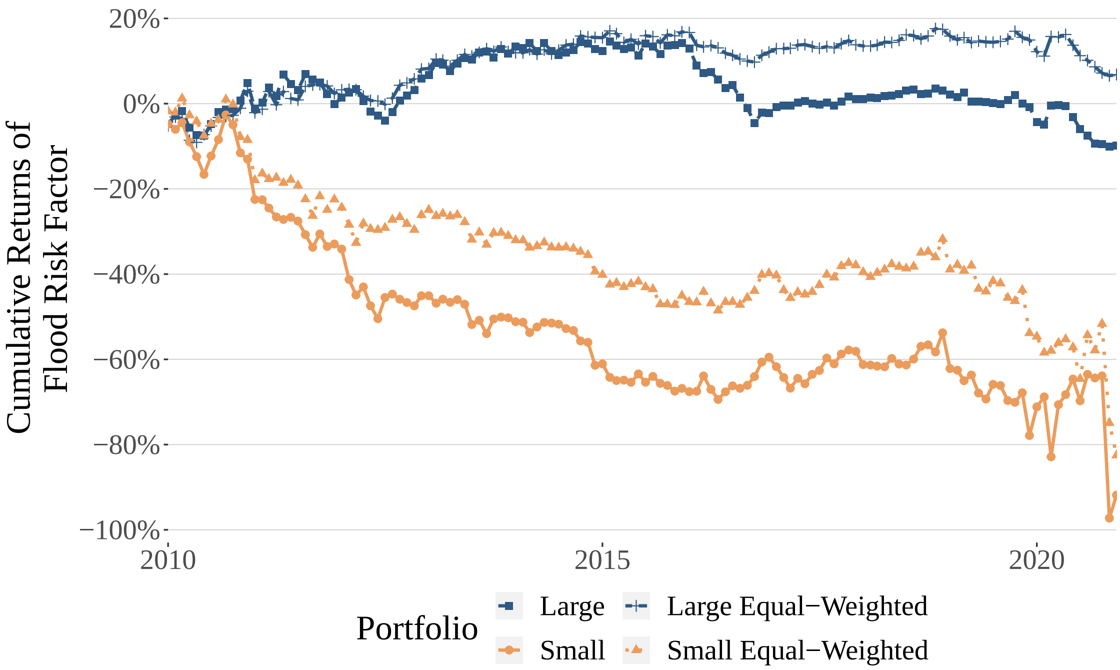


Figure 7: Cumulative Return of the Exposure-Weighted Flood Factor for Size-sorted Samples. The orange solid and dotted lines plot the cumulative returns of the flood factor from the sample restricted to small banks. The solid line is the exposure-weighted cumulative return and the dotted line is the equally-weighted returns. The two blue lines plot large banks' exposure-weighted cumulative return (two-dash) and equal-weighted cumulative return (dashed).

Table 1:
Summary Statistics

This table provides sample means of the main variables used in the analysis. Means are computed for two distinct samples sorted and split on the BHCs' flood risk exposure measure. Banks with a flood risk exposure below the fourth quartile are defined as 'Low', while banks in the fourth quartile belong to the group 'High'. Ratios are reported in %. Mortgage-based variables come from a bank-year panel, while bank balance sheet information is available at the quarterly level, and stock returns are monthly. Means and differences are computed at the respective frequencies to avoid repetitions. The *Flood Risk Exposure* is a weighted average of regional flood probabilities, where the weights are based on banks' mortgage lending activity. The first measure is based on flood probabilities by 2050, while the second has a 2035 horizon. The third uses risk scores assigned to counties.

	High Exposure		Low Exposure				
	Mean	Obs	Mean	Obs.	Diff.	t-Stat	Signif.
Mortgage-based Variables							
Application (Mn $)	129.7	1,721	176.0	5,157	−46.3	−1.3	
Retained Amount (Mn $)	56.4	1,721	83.0	5,157	−26.7	−1.4	
Active Counties	101.2	1,721	115.7	5,157	−14.5	−1.9	*
Active States	7.9	1,721	8.9	5,157	−1.0	−3.2	***
Average Origination (Thsd $)	519.7	1,721	516.4	5,157	3.3	0.1	
Average Retained (Thsd $)	0.1	1,721	0.1	5,157	−0.03	−1.4	
Flood Risk Exposure (2050)	20.7	1,721	7.9	5,157	12.8	49.9	***
Flood Risk Exposure (2035)	19.0	1,721	7.6	5,157	11.5	55.3	***

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Table 1 – *Continued from previous page*

	Low Exposure		High Exposure				
	Mean	Obs	Mean	Obs.	Diff.	t-Stat.	Signif.
Flood Risk (Score-based)	2.4	1,721	1.4	5,157	1.0	53.6	***
Insurance Policies	11,293.2	1,721	3,563.7	5,157	7,729.6	11.5	***
Insurance Sum (Mn$)	2,322.5	1,721	725.8	5,157	1,596.7	11.6	***
Stock Variables							
Return	0.3	8,248	0.4	71,911	−0.1	−1.1	
Excess Return	0.1	8,248	0.3	71,911	−0.1	−1.0	
Balance Sheet Variables							
Total Assets (Bn)	20.5	5,909	50.7	16,511	−30.2	−12.4	***
Loan Ratio	68.0	5,909	68.1	16,511	−0.1	−0.4	
Tier 1 Leverage	10.6	5,909	10.0	16,511	58.1	1.1	
Deposit Ratio	77.3	5,909	75.4	16,511	1.9	11.6	***
Real Estate Loans Ratio	45.3	5,909	44.8	16,511	0.4	1.9	*
Mortgage Ratio	19.0	5,909	18.6	16,511	0.3	2.1	**
ROA	0.4	5,909	0.4	16,511	0.003	0.2	
NPL Ratio	1.2	5,909	1.2	16,511	0.02	0.8	
Z-score	21.9	5,909	29.6	16,511	−7.7	−4.8	***

Table 2:
Flood Disasters and Return on Assets of Bank Subsidiaries

This Table reports results from regressing bank-level returns on assets on bank-level exposure to flood disasters. The main explanatory variable is the *Flood Damage Exposure*, which captures banks' exposure to flood disasters. The measure is based on property damage estimates from SHELDUS available at the county-month level and is aggregated at the bank level using a bank's mortgage lending activity. Controls include the lag of the capital ratio, log(Employees), log(Total Assets) and RoA. Bank level data comes from the FDIC SDI database. Disaster damage estimations from Sheldus are divided by county level total personal income from the Census Bureau ACS. Deposit Exposure weighs the damage estimates with bank level local exposure proxied by branch deposits. Office exposure weighs the property damage by the number of offices. Standard errors are clustered at the bank holding company level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Baseline

	RoA_{t+1}		
	(1)	(2)	(3)
(Intercept)	0.445***		
	(3.07)		
Flood Damage Exposure	-0.006***	-0.005***	-0.004**
	(-3.77)	(-2.76)	(-2.25)
Capital Ratio	0.002*	0.001	-0.010***
	(1.94)	(0.798)	(-5.02)
log(Employees)	0.065***	0.070***	0.365*
	(2.83)	(4.00)	(1.87)
log(Assets)	-0.055**	-0.066***	-0.352**
	(-2.22)	(-3.28)	(-2.20)
RoA	0.895***	0.889***	0.628***
	(12.9)	(12.1)	(12.2)
Quarter FE		YES	YES
Bank FE			YES
Obs.	230,078	230,078	230,078
R^2	0.663	0.670	0.735
Within R^2		0.655	0.370

Panel B: Different Damage Measures

	RoA_{t+1}		
	Ratio	Deposit-weighted	Office-weighted
Flood Damage Exposure	-0.005***	-0.003	-0.003
	(-5.30)	(-1.52)	(-1.52)
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Quarter FE	YES	YES	YES
Obs.	230,078	230,078	230,078
R^2	0.73	0.73	0.73
Within R^2	0.37	0.37	0.37

Table 3:
Bank performance and Flood Damage Exposure

This table reports the results from pooled-OLS regressions with fixed effects. The main explanatory variable is the *Flood Damage Exposure*, which captures banks' exposure to flood disasters. The measure is based on property damage estimates from SHELDUS available at the county-month level and is aggregated at the bank level using a bank's mortgage lending activity. The dependent variables are one-quarter ahead measures. Leverage and capital ratio are based on Tier 1 capital. Stable wholesale funding ratio (*SWFR*), non-performing loans, charge-offs, and loan-loss provisions are divided by the total loans. *Z-Score* is a proxy for a bank's default probability. Standard errors are clustered at the bank level. t-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

	ROA_{t+1}	Leverage_{t+1}	Capital Ratio_{t+1}	SWFR_{t+1}	Z-Score_{t+1}	NPL_{t+1}	Charge-Offs_{t+1}	Loan Loss_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)	(7) c	(8)
Flood Damage Exposure	-0.005***	-0.022***	-0.018**	-0.049***	-0.011***	0.002	0.0002	0.013***
	(-3.92)	(-3.16)	(-2.56)	(-11.3)	(-2.93)	(0.405)	(0.902)	(3.44)
ROA	0.248***							
	(4.78)							
Capital Ratio			1.13***					
			(21.3)					
SWFR				0.638***				
				(40.3)				
Z-Score					0.859***			
					(26.8)			
NPL						0.843***		
						(31.4)		

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Table 3 – *Continued from previous page*

	ROA_{t+1}	Leverage_{t+1}	Capital Ratio_{t+1}	SWFR_{t+1}	Z-Score_{t+1}	NPL_{t+1}	Charge-Offs_{t+1}	Loan Loss_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Charge-Offs							0.369***	
							(15.5)	
Loan Loss								0.362***
								(9.28)
Leverage	0.002	0.023	-1.19***	-0.003	-0.009	-0.0002	-0.0002	-0.001
	(0.975)	(0.470)	(-13.0)	(-0.887)	(-0.973)	(-0.120)	(-0.942)	(-0.869)
log(Assets)	-0.227***	-1.62***	-1.31***	1.36***	-0.007	0.430***	0.0004	0.251***
	(-4.25)	(-4.68)	(-3.88)	(6.56)	(-0.093)	(6.34)	(0.068)	(5.95)
Loan Ratio	0.060	2.28	6.87***	-3.09***	-0.550	1.11***	-0.004	0.706***
	(0.283)	(1.53)	(3.22)	(-3.15)	(-1.13)	(3.60)	(-0.152)	(4.06)
Mortgage Ratio	-0.033	-6.78*	-10.1**	-0.530	0.051	-0.661	0.086**	-0.622***
	(-0.106)	(-1.66)	(-2.22)	(-0.349)	(0.105)	(-1.62)	(2.27)	(-2.93)
Bank	YES	YES	YES	YES	YES	YES	YES	YES
Quarter	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	15,012	14,485	14,475	15,012	9,053	15,012	14,438	15,010
R^2	0.493	0.886	0.892	0.840	0.984	0.855	0.495	0.560
Within R^2	0.054	0.004	0.056	0.439	0.733	0.623	0.124	0.121

Table 4:
Examination of Heterogeneity in Bank Returns on Assets

This table partitions the results from Table 3 on mortgage loan share (High and Low) and bank size (Small and Large). The main explanatory variable is the *Flood Damage Exposure*, which captures banks' exposure to flood disasters. The measure is based on property damage estimates from SHELDUS available at the county-month level and is aggregated at the bank level using a bank's mortgage lending activity. The dependent variables are one-quarter ahead measures. Bank controls include the lagged dependent variables, leverage, log(assets), loan ratio, and mortgage loan share. Standard errors are clustered at the bank level. *t*-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Returns on Assets

	Mortgage Loan Share		Size	
	High	Low	Small	Large
	(1)	(2)	(3)	(4)
Flood Damage Exposure	-0.011*	-0.004***	-0.004***	-0.009***
	(-1.85)	(-3.88)	(-8.73)	(-3.71)
Bank Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Obs.	8,707	6,304	6,119	8,892
R^2	0.461	0.567	0.466	0.528

Panel B: Non-Performing Loans

	Mortgage Loan Share		Size	
	High	Low	Small	Large
	(1)	(2)	(3)	(4)
Flood Damage Exposure	0.018*	0.0010	-0.003*	0.016***
	(1.90)	(0.169)	(-1.85)	(4.17)
Bank Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Obs.	8,707	6,304	6,119	8,892
R^2	0.868	0.865	0.857	0.863

Panel C: Loan Charge-Offs

	Mortgage Loan Share		Size	
	High	Low	Small	Large
	(1)	(2)	(3)	(4)
Flood Damage Exposure	0.002**	-4×10^{-5}	0.0001	0.0003
	(2.31)	(-0.268)	(0.660)	(1.22)
Bank Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Obs.	8,403	6,034	6,106	8,331
R^2	0.514	0.541	0.478	0.525

Table 5:
Flood Risk Exposure and the Cross-section of Bank Stock Returns

This Table reports results from regressing bank-level excess return on the flood risk exposure. The baseline exposure is based on flood risk by 2050. Column (2) uses flood risk by 2035 using a second variable provided by First Street Foundation. Similarly, in column (3), the exposure measure is based on risk scores assigned to the county rather than probabilities. Nb-weighted uses the number of mortgages rather than mortgage amounts when computing the local exposure measure. Securitised and sold use mortgages securitized and sold rather than retained. The flood risk exposure in the final column is constructed using the local mortgage concentration and therefore captures a different channel. The dependent variable is the difference between the bank stock return and the risk-free rate. Bank balance sheet data comes from Call Reports. Equity data from CRSP. The Flood Risk Exposure is based on county-level flood risk from First Street Foundation and is aggregated at the bank level using the local mortgage activity of a bank from the Home Mortgage Disclosure Act (HMDA) data. Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

	Excess Returns							
	2050 Flood Risk	2035 Flood Risk	Flood Risk Score	Number-weighted	Origination-weighted	Rolling Retained	Rolling Origination	Competition-weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood Risk Exposure	-0.174***	-0.178***	-0.133**	-0.185***	-0.173***	-0.159**	-0.182***	0.019
	(-3.03)	(-3.11)	(-2.05)	(-3.21)	(-3.28)	(-2.46)	(-3.10)	(0.657)
Leverage	-0.002	-0.002	-0.003	-0.002	-0.002	-0.002	-0.002	-0.003
	(-0.662)	(-0.747)	(-0.913)	(-0.632)	(-0.691)	(-0.678)	(-0.696)	(-0.955)
log(Assets)	-3.02***	-3.03***	-3.02***	-3.03***	-3.03***	-3.02***	-3.03***	-3.01***
	(-15.1)	(-15.1)	(-15.1)	(-15.1)	(-15.2)	(-15.1)	(-15.1)	(-15.2)

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Table 5 – *Continued from previous page*

	Excess Returns							
	2050 Risk	2035 Risk	Risk Score	Number-weighted	Origination-weighted	Rolling Retained	Rolling Origination	Competition-weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan Ratio	-1.14	-1.14	-1.13	-1.16	-1.15	-1.14	-1.16	-1.13
	(-1.56)	(-1.56)	(-1.55)	(-1.58)	(-1.59)	(-1.56)	(-1.59)	(-1.59)
Mortgage Ratio	1.54***	1.55***	1.55***	1.55***	1.54***	1.58***	1.58***	1.47**
	(2.66)	(2.69)	(2.67)	(2.68)	(2.66)	(2.73)	(2.75)	(2.50)
log(BE/ME)	2.86***	2.87***	2.86***	2.87***	2.86***	2.86***	2.87***	2.84***
	(15.8)	(15.8)	(15.7)	(15.7)	(15.9)	(15.7)	(15.7)	(15.9)
Return	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***
	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)
Mortgage Exposure	-1.48***	-1.50***	-1.52***	-1.48***	-1.48***	-1.56***	-1.60***	-1.34***
	(-3.54)	(-3.57)	(-3.58)	(-3.54)	(-3.51)	(-3.66)	(-3.70)	(-3.23)
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	43,227	43,227	43,227	43,227	43,227	43,227	43,227	43,227
R^2	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28

Table 6:
Examination of Heterogeneity in Stock Returns

This table reports the results from pooled-OLS regressions with fixed effects. The main explanatory variable is the *Flood Risk Exposure*, which captures banks' exposure to flood risk. The measure is based on a flood probability map from First Street Foundation available at the county level and is aggregated at the bank level using a bank's mortgage lending activity. The dependent variable is the excess return. All regressions include bank-level controls, such as log(book-to-asset), Tier 1 leverage, mortgage ratio, loan ratio, log(assets), past-month return, and mortgage exposure. Standard errors are clustered at the bank level. t-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Mortgage Loan Share

	Excess Returns		
Sample	High	Low	Full
	(1)	(2)	(3)
Flood Risk Exposure	-0.241***	-0.126	-0.118
	(-3.13)	(-1.55)	(-1.50)
High RE			0.288**
			(1.99)
Flood Risk Exposure × High RE			-0.113
			(-1.12)
Bank Controls	YES	YES	YES
Month FE	YES	YES	YES
Obs.	20,706	22,521	43,227
R^2	0.248	0.325	0.283

Panel B: Bank Size

	Excess Returns		
Sample	Small	Large	Full
	(1)	(2)	(3)
Flood Risk Exposure	-0.295***	0.008	-0.024
	(-3.81)	(0.100)	(-0.280)
Small			0.947***
			(5.48)
Flood Risk Exposure × Small			-0.251**

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Table 6 – *Continued from previous page*

			(-2.31)
Bank Controls	YES	YES	YES
Month FE	YES	YES	YES
Obs.	23,383	19,844	43,227
R^2	0.198	0.457	0.284

Panel C: Flood Risk Exposure

	Excess Returns		
	High	Low	Full
	(1)	(2)	(3)
Flood Risk Exposure	-0.177***	0.069	0.302
	(-2.91)	(0.313)	(1.40)
High Flood			-0.313**
			(-2.21)
Flood Risk Exposure × High Flood			-0.488**
			(-2.22)
Bank Controls	YES	Yes	Yes
Month FE	Yes	Yes	Yes
Obs.	23,273	19,954	43,227
R^2	0.311	0.266	0.283

Table 7:
Risk-adjusted Returns on Flood Risk sorted Portfolios

This table presents estimates from OLS regression of monthly value-weighted excess returns on each Flood Risk Exposure-sorted portfolio of bank on holding companies on the Carhart (1997) four-factor model and two bond risk factors from Gandhi and Lustig (2015). *crd* is the excess return on an index of investment-grade corporate bonds, while *ltg* is the excess return on an index of long-term government bonds. High-Low is a portfolio that goes long the high exposure portfolio and short the low flood exposure portfolio. Standard errors are Newey-West adjusted with three lags. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Full Sample

	Risk-adjusted Returns				High-Low
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.377	0.054	0.112	0.045	-0.434***
	(1.28)	(0.208)	(0.492)	(0.178)	(-3.27)
Mkt - R_f	0.537***	0.596***	0.634***	0.609***	0.074
	(8.46)	(12.1)	(10.5)	(10.7)	(1.51)
SMB	0.543***	0.561***	0.530***	0.556***	0.016
	(4.92)	(6.00)	(5.88)	(5.80)	(0.237)
HML	0.606***	0.612***	0.737***	0.681***	0.072
	(7.21)	(7.11)	(9.12)	(7.31)	(1.34)
Mom	-0.145*	-0.070	-0.051	-0.063	0.080**
	(-1.96)	(-0.968)	(-0.824)	(-0.861)	(2.14)
ltg	-0.539***	-0.219**	-0.127	-0.225**	0.310***
	(-3.48)	(-2.29)	(-0.989)	(-2.27)	(3.96)
crd	0.365	-0.217	-0.338	-0.257	-0.610***
	(1.34)	(-0.947)	(-1.35)	(-1.18)	(-3.81)
Obs.	190	190	190	190	190
R^2	0.71	0.78	0.80	0.78	0.15

Panel B: Small Banks

	Risk-adjusted Returns				High-Low
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.739**	0.235	0.131	0.067	-0.774***
	(2.16)	(0.737)	(0.453)	(0.216)	(-3.76)
Factors	YES	YES	YES	YES	YES
Obs.	190	190	190	190	190
R^2	0.57	0.61	0.61	0.63	0.14

Panel C: Large Banks

	Risk-adjusted Returns				High-Low
(Intercept)	-0.067	0.101	-0.017	0.044	0.009
	(-0.225)	(0.320)	(-0.058)	(0.148)	(0.062)
Factors	YES	YES	YES	YES	YES
Obs.	190	190	190	190	190
R^2	0.74	0.76	0.77	0.75	0.05

Table 8:
Performance of the Exposure-Weighted Flood Factor

This table reports monthly time-series regressions using data from January 2005 to December 2020. The dependent variable is the return on the exposure-weighted flood factor. Mkt is the market return. SMB and HML are the size and value factors of Fama and French (1993). Mom is the momentum factor of Carhart (1997). Returns are in percent per month. Standard errors are clustered Newy-West adjusted with three lags. t-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Full Sample

	Flood Factor			
	(1)	(2)	(3)	(4)
(Intercept)	-0.237*	-0.206	-0.234*	-0.243*
	(-1.89)	(-1.60)	(-1.79)	(-1.86)
Mkt		-0.017	0.003	0.014
		(-0.586)	(0.087)	(0.416)
SMB			-0.058	-0.055
			(-0.988)	(-0.940)
HML			-0.037	-0.011
			(-0.762)	(-0.212)
Mom				0.044
				(1.33)
Obs.	192	190	190	190
R^2		0.002	0.013	0.022

Panel B: Small Banks

	Flood Factor			
	(1)	(2)	(3)	(4)
(Intercept)	-0.563**	-0.556**	-0.558**	-0.579**
	(-2.10)	(-2.46)	(-2.43)	(-2.53)
Factors	None	Mkt	Mkt, SMB, HML	Mkt, SMB, HML, Mom
Obs.	192	190	190	190
R^2		0.034	0.040	0.056

Panel C: Large Banks

	Flood Factor			
	(1)	(2)	(3)	(4)
(Intercept)	0.015	-0.018	0.022	0.019
	(0.091)	(-0.105)	(0.129)	(0.109)
Factors	None	Mkt	Mkt, SMB, HML	Mkt, SMB, HML, Mom
Obs.	192	190	190	190
R^2		0.006	0.018	0.019

Table 9:
Flood Disasters as Sources of Flood Factor Performance

This Table reports results from regressing the monthly return of the flood factor on different measures of flood disasters. The flood factor is constructed as a long-short portfolio that goes long banks with large exposure to flood risk and short banks with low risk. Weights are based on banks' exposure to flood risk. Returns are in percent. The variable *Flood Damage* is the sum of flood-related property damage estimates in a given month across the United States and comes from SHELDUS. *High Damage* is an indicator variable with a value of 1 if the estimated monthly damages are with the top decile. In column (3), extitTotal Damage are damage estimates for all hazard types. Standard errors are Newy-West adjusted with three lags. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $* * *$:$p < 0.01$

Panel A: Full Sample

	Flood Factor		
	(1)	(2)	(3)
(Intercept)	-0.211	-0.165	-0.212
	(-1.54)	(-1.06)	(-1.55)
Δlog(Flood Damage)	-0.107**		
	(-2.32)		
High Damage		-0.389	
		(-1.08)	
Δ log(Total Damage)			-0.094**
			(-2.09)
Obs.	180	180	180
R^2	0.029	0.005	0.024

Panel B: Small Banks

	Flood Factor		
	(1)	(2)	(3)
(Intercept)	-0.565**	-0.528**	-0.565**
	(-2.55)	(-2.29)	(-2.56)
Δ log(Flood Damage)	-0.071		
	(-0.887)		
High Damage		-0.306	
		(-0.391)	
Δ log(Total Damage)			-0.066
			(-0.873)
Obs.	180	180	180
R^2	0.005	0.001	0.005

Table 10:
Flood Risk Exposure without Disaster Periods

This Table reports results from regressing bank equity returns on the main flood risk exposure for different samples. Columns (1) and (2) remove periods around Hurricane Katrina (August 2005) and other major storms. Column (3) focuses on banks that have a damage exposure measure of zero. Column (4) restricts the sample further to banks with a high flood risk exposure but experiencing no damages from floods in a given month. Disasters data comes from Sheldus. All regressions include the bank level controls log(Assets), log(Market Equity), Capital Ratio, and previous month's return. The dependent variable is the difference between the bank stock return and the risk-free rate. Bank balance sheet data comes from Call Reports. Equity data from CRSP. The sample runs from 2004 to 2020. Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks

	Excess Returns			
	Without Hurricane Katrina	Without Major Storms	Zero Damage	Zero Damage & High-Risk
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.130***	-0.137***	-0.210***	-0.185
	(-2.59)	(-2.71)	(-2.65)	(-1.44)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	58,861	57,274	14,371	3,433
R^2	0.306	0.305	0.261	0.339

Panel B: Small Banks

	Excess Returns			
	Without Hurricane Katrina	Without Major Storms	Zero Damage	Zero Damage & High-Risk
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.179***	-0.185***	-0.267**	-0.236
	(-2.68)	(-2.78)	(-2.58)	(-1.29)
Bank Controls	YES	YES	YES	YES

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Table 10 – *Continued from previous page*

Month FE	YES	YES	YES	YES
Obs.	29,238	28,562	9,905	2,500
R^2	0.208	0.207	0.223	0.312

Panel C: Large Banks

	Excess Returns			
	Without Hurricane Katrina	Without Major Storms	Zero Damage	Zero Damage & High-Risk
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.047	-0.054	-0.029	0.032
	(-0.615)	(-0.687)	(-0.265)	(0.219)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	29,623	28,712	4,466	933
R^2	0.484	0.482	0.450	0.556

Table 11:
Bank Stock Returns and Disaster Realizations

This Table reports results from regressing bank equity returns on the main flood risk exposure and controlling for realized flood disasters. Disasters data comes from Sheldus. Damage Exposure is a weighted average of property damage estimates, where the weights are given by a bank's mortgage lending activity. High Damage is an indicator variable equal to 1 if the Damage Exposure is in the top quartile. Total Damage is the unweighted dollar amount of damages that occurred in the United States in a given month. All regressions include bank controls, macro controls, and an intercept. The bank level controls include log(Assets), log(Market Equity), and Capital Ratio. Macro controls are log(GDP), CPI, PCPI, and the unemployment rate. The dependent variable is the difference between the bank stock return and the risk-free rate. Bank balance sheet data comes from Call Reports. Equity data from CRSP. Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks

	Excess Returns				Return Residuals
Flood Damages	Weighted Damages		High Damage	Total Damages	Weighted Damages
	(1)	(2)	(3)	(4)	(5)
Flood Risk Exposure	-0.118**	-0.118**	-0.150**	-0.124**	-0.091*
	(-2.00)	(-2.00)	(-2.52)	(-2.10)	(-1.75)
Flood Damages	-0.085***	-0.084***	-0.238*	-0.199***	
	(-3.81)	(-2.72)	(-1.69)	(-9.46)	
Flood Risk Exposure		-0.001	0.338**	-0.016	
× Flood Damages		(-0.078)	(2.09)	(-0.654)	
Obs.	50,957	50,957	50,957	50,957	50,957
R^2	0.054	0.054	0.054	0.055	0.033

Panel B: Small Banks

	Excess Returns				Return Residuals
Flood Damages	Weighted Damages		High Damage	Total Damages	Weighted Damages
	(1)	(2)	(3)	(4)	(5)

Continued on next page

Table 11 – *Continued from previous page*

Flood Risk Exposure	-0.200***	-0.200***	-0.223***	-0.202***	-0.180**
	(-2.59)	(-2.59)	(-2.68)	(-2.60)	(-2.53)
Flood Damages	-0.002	0.004	-0.550**	-0.141***	
	(-0.067)	(0.080)	(-2.41)	(-4.20)	
Flood Risk Exposure		-0.004	0.347*	0.002	
× Flood Damages		(-0.254)	(1.87)	(0.077)	
Obs.	24,677	24,677	24,677	24,677	24,677
R^2	0.059	0.059	0.059	0.059	0.038

Panel B: Large Banks

	Excess Returns				Return Residuals
Flood Damages	Weighted Damages		High Damage	Total Damages	Weighted Damages
	(1)	(2)	(3)	(4)	(5)
Flood Risk Exposure	0.031	0.033	0.003	0.018	0.025
	(0.313)	(0.331)	(0.032)	(0.181)	(0.281)
Flood Damages	-0.116***	-0.101***	-0.212	-0.252***	
	(-5.42)	(-4.12)	(-1.20)	(-10.4)	
Flood Risk Exposure		-0.021	0.220	-0.051	
× Flood Damages		(-1.54)	(0.910)	(-1.49)	
Obs.	26,280	26,280	26,280	26,280	26,280
R^2	0.057	0.057	0.057	0.058	0.033

Table 12:
Bank Stock Returns and Climate Change Concerns

This Table reports results from regressing bank equity returns on the main flood risk exposure and controlling for changes in climate change concerns. SVI variables are from the Google Search index. UMC are the unexpected media climate change concerns and are prediction errors from AR(1) regression model following Ardia et al. (2022). The dependent variable is the difference between the bank stock return and the risk-free rate. All regressions include bank controls such as log(Assets), log(BE/ME), Tier 1 leverage, and the previous month's stock return, as well as macro controls (log(GDP), lo(PCE), log(PCPI), the unemployment rate, and ΔVIX). Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Full Sample

	Excess Returns				
	SVI: Climate Change	SVI: Flood	UMC: Aggregate	UMC: Flood	UMC: Summits
	(1)	(2)	(3)	(4)	(5)
Flood Risk Exposure	-0.155**	-0.150**	-0.144*	-0.144*	-0.147*
	(-2.44)	(-2.36)	(-1.72)	(-1.72)	(-1.76)
ΔCC	-0.139***	-0.761***	-0.461***	-0.032	-0.424***
	(-3.22)	(-11.8)	(-6.86)	(-0.600)	(-4.98)
Flood Risk Exposure	0.005	-0.161***	0.085	0.104*	0.078
$\times$ ΔCC	(0.136)	(-2.95)	(1.08)	(1.77)	(0.869)
Obs.	42,499	42,499	35,008	35,008	35,008
R^2	0.075	0.080	0.074	0.073	0.074

Panel B: Small Banks

	Excess Returns				
	SVI: Climate Change	SVI: Flood	UMC: Aggregate	UMC: Flood	UMC: Summits
	(1)	(2)	(3)	(4)	(5)
Flood Risk Exposure	-0.262***	-0.262***	-0.295***	-0.293***	-0.298***
	(-3.37)	(-3.35)	(-3.27)	(-3.24)	(-3.32)
ΔCC	-0.054	-0.350***	-0.634***	-0.348***	-0.750***
	(-0.824)	(-4.23)	(-7.01)	(-4.45)	(-6.57)
Flood Risk Exposure	-0.042	-0.187***	0.002	0.024	-0.010
$\times$ ΔCC	(-0.759)	(-2.85)	(0.016)	(0.331)	(-0.088)
Obs.	24,010	24,010	20,423	20,423	20,423
R^2	0.073	0.074	0.078	0.077	0.079

Table 13:
Bank Stock Returns and Local Real Estate Markets

This Table reports results from regressing bank equity returns on the main flood risk exposure and controlling for local flood insurance or foreclosures. All regressions including bank controls and month fixed effects. The bank level controls include log(Assets), log(Market Equity), and Capital Ratio. Macro controls are log(GDP), CPI, PCPI, and the unemployment rate. The dependent variable is the difference between the bank stock return and the risk-free rate. Bank balance sheet data comes from Call Reports. Equity data from CRSP. Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Full Sample

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.163***	-0.166***	-0.187**	-0.185**
	(-2.78)	(-2.81)	(-2.47)	(-2.46)
Flood Policies	-0.035			
	(-0.642)			
Flood Claim Amount		-0.090*		
		(-1.76)		
Foreclosures			0.053	
			(1.34)	
Defaults				-0.038**
				(-2.23)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	43,227	43,227	31,785	31,785
R^2	0.28	0.28	0.24	0.24

Panel B: Small Banks

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.290***	-0.285***	-0.311***	-0.304***
	(-3.68)	(-3.68)	(-3.20)	(-3.29)
Flood Policies	-0.014			
	(-0.076)			

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Table 13 – *Continued from previous page*

Flood Claim Amount		-0.192**		
		(-2.06)		
Foreclosures			0.137***	
			(2.60)	
Defaults				-0.010
				(-0.389)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	23,648	23,648	19,126	19,126
R^2	0.20	0.20	0.20	0.20

Panel C: Large Banks

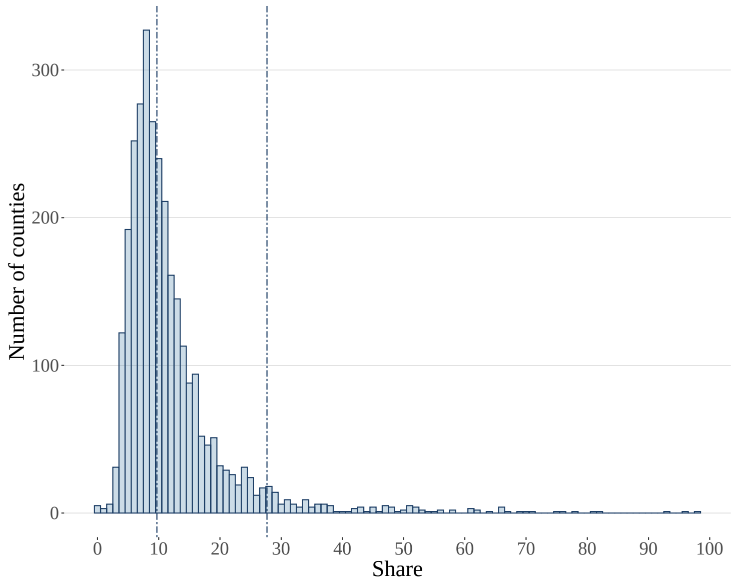
Dependent Variable:	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	0.038	0.016	0.028	0.039
	(0.482)	(0.193)	(0.241)	(0.342)
Flood Policies	-0.058*			
	(-1.66)			
Flood Claim Amount		-0.038		
		(-0.765)		
Foreclosures			-0.081	
			(-1.47)	
Defaults				-0.040*
				(-1.77)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	19,968	19,968	12,878	12,878
R^2	0.46	0.46	0.40	0.40

Table 14:
Regional Factors and Bank Stock Returns

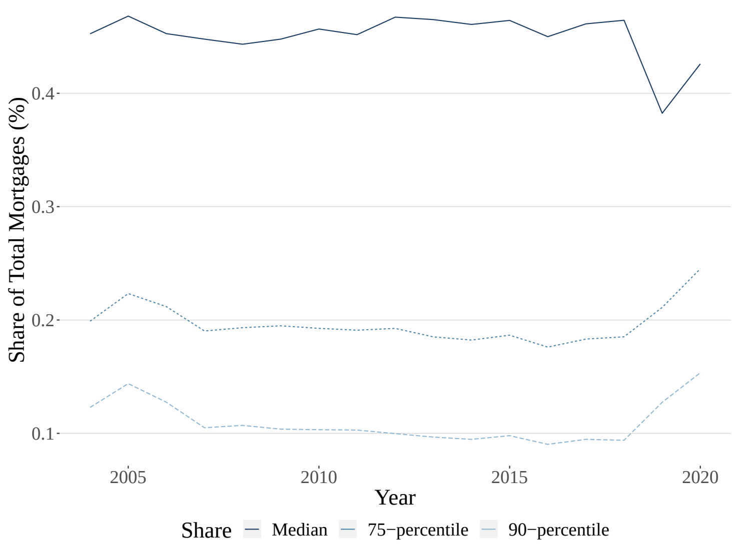
This Table reports results from regressing bank equity returns on the main flood risk exposure and controlling for general regional exposure. Column (1) includes state-level controls (GDP growth, inflation, unemployment rate, and the change in the house price index) weighted by the bank's exposure measure. Column(2) includes state dummies. For each state, the variable takes a value of 1 if the bank has originated mortgages in that state. Column (3) interacts the state dummies with year-dummies. Column(4) includes headquarter-state fixed effects. All regressions include the bank level controls Tier 1 leverage, log(assets), loan ratio, mortgage loan ratio, log(market equity), and lagged return. The dependent variable is the difference between the bank stock return and the risk-free rate. Bank balance sheet data comes from Call Reports. Equity data from CRSP. Standard errors are clustered at the bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks				
	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.238***	-0.148**	-0.164**	-0.122*
	(-3.49)	(-2.37)	(-2.53)	(-1.84)
Obs.	38,507	43,227	43,227	43,227
R^2	0.25	0.28	0.30	0.28
Panel B: Small Banks				
	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.389***	-0.254***	-0.282***	-0.195**
	(-4.47)	(-3.02)	(-2.96)	(-2.17)
Obs.	22,869	23,648	23,648	23,648
R^2	0.19	0.20	0.22	0.20
Panel C: Large Banks				
	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	0.051	0.012	0.023	-0.031
	(0.480)	(0.133)	(0.246)	(-0.314)
Obs.	16,024	19,968	19,968	19,968
R^2	0.40	0.46	0.48	0.46
Bank Controls	YES	YES	YES	YES
State Controls	YES	NO	NO	NO
State Dummies	NO	YES	NO	NO
State-Year Dummies	NO	NO	YES	NO
Month FE	YES	YES	YES	YES
HQ FE	NO	NO	NO	YES

A1. Additional Figures



a) Number of Counties by Risk Group



b) Share of Mortgage Amounts by Risk Percentiles

Figure A1.1: Counties and Mortgage Amounts by Flood Risk Groups. Panel (a) plots the histogram of counties as a function of their flood risk measure. Share is the percent of properties at a 1% flood risk i.e., risk of a 100-year flood. The figure uses data from the First Street Foundation. Panel (b) plots the share of total mortgage origination (from HMDA) at three different risk percentiles. The percentiles are based on the same flood risk measure.

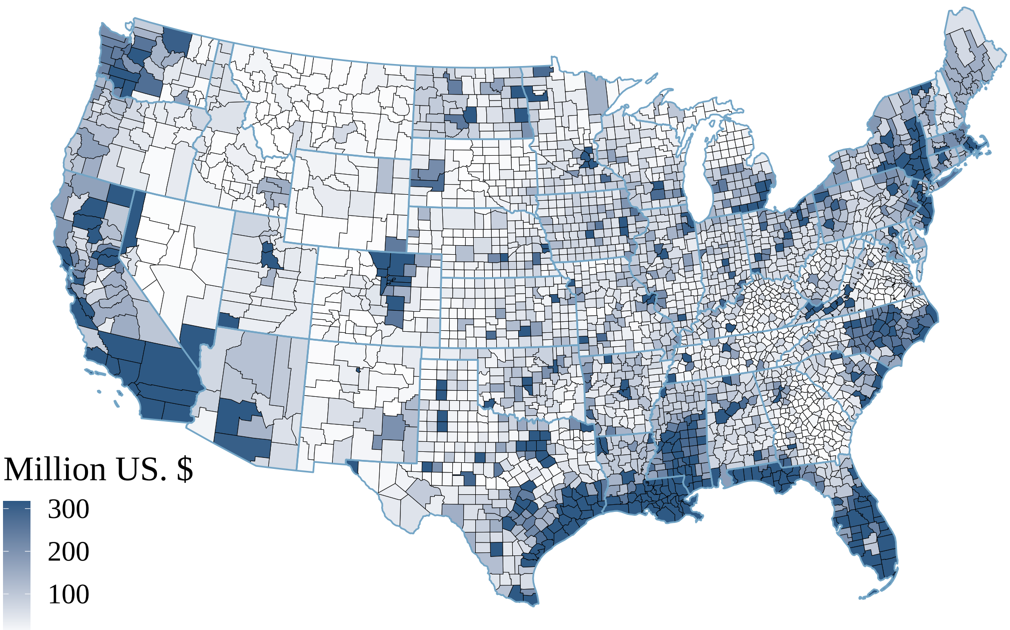


Figure A1.2: Property Damages from Floods. This figure plots the estimated property damages from floods since 1960 in the United States. The estimates come from SHELDUS and are available at the county level.

A2. Systematic Risk Decomposition

In the previous subsection, I introduced the flood risk factor and analyzed this factor together with the other risk factors. In the next step, I will identify the underlying risk exposures of bank stock returns to the different (risk) factors. As these factors are analyzed simultaneously within a time-varying regression setup, I can perform a variance decomposition following Klein and Chow (2013). The technique borrows an approach from the physics literature and consists in computing an orthogonalization of the factors of interest. This approach boasts several advantages over other risk decomposition procedures. First, it addresses the correlation between the variables with a symmetric procedure that identifies the underlying uncorrelated components for each factor simultaneously and not sequentially. Hence, the process eliminates any impact of the choice of a particular starting vector. Second, Klein and Chow (2013) show that the symmetric decomposition technique is superior to the often used Principal Component Analysis (PCA) in maintaining a maximum resemblance between the original factors and transformed factor using the sequential orthogonalization procedure. The orthogonalized components of factors retain their variances, while their cross-sectional correlations are equal to zero. Further, using the orthogonalized factors in a multi-factor regression leads to the same regression R^2, as using the original (non-orthogonalized) factors. The method allows disentangling the R-squared based on the factors' volatilities and their corresponding betas to decompose the systematic risk into separate contributions. In the first step, the methodology consists of running the regression in A2.1, where the orthogonalized risk factors and their related beta coefficients are given by $F^{\perp}_{T\times K}$ and $\beta^{\perp}$.

$$r_{j,t} - r_{f,t} = \alpha + \beta^{\perp}_{j} F^{\perp}_{t} + \epsilon_{j,t} \tag{A2.1}$$

where j represents the portfolio of interest.

Second, using the estimate of $\beta^{\perp}_{j}$, the coefficient of determination, R^2, can be decomposed into the individual decomposed systemic risk. Because of the orthogonalization procedure, the decomposition can be defined as follows:

$$R^2 = \sum_{k=1}^{K} DR^2_k, \text{ where } DR^2_k = \left(\hat{\beta}^{\perp}_{k} \frac{\sigma_k}{\sigma_r}\right)^2 \tag{A2.2}$$

where σ_k is the standard deviation of factor k, and σ_r is the standard deviation of the dependent variable. The matrix $F^{\perp}_{T\times K}$ is derived following the steps in Klein and Chow (2013). It is defined as:

$$F^{\perp}_{T\times K} = F_{T\times K} S_{K\times K} \tag{A2.3}$$

where $F_{T\times K}$ are the original factors and $S_{K\times K}$ is a symmetric matrix that represents the inverse of the correlation matrix between the original and orthogonalized factors. In short, it is a linear combination of the eigenvector matrix and eigenvalues of the original factors.[17]. I estimate $F^{\perp}_{T\times K}$ for every subsample separately and use a fixed rolling window of 48 months to conduct time-varying democratic variance decompositions for analyzing the relative factor contributions over time.

The time-varying variance decompositions for the two portfolios sorted on their flood risk are provided in the first row of figure A2.1. In general, we see that the risk factors can explain a considerable share of the portfolios' return variance. Second, the figure makes it clear that there exists considerable time variation in the explanatory power. The total R^2 lies between 75% to 85% over the sample in consideration. Next, the largest fraction over the full sample is explained by the market risk factor. Its contribution is also the most consistent across the different factors under consideration. Further looking at similarities between the figures for the 'High Flood' and 'Low Flood' portfolios, we see that the value factor is a relatively important factor for both samples, explaining roughly a fifth of the variation. Its importance decreases in the middle of the last decade. Importantly there is no clear difference between the High Flood and Low Flood samples suggesting that the sample does not differ in its integration with the market. The size factor also exhibits a very similar pattern in both samples. It's almost irrelevant in the first half. In either sample, the flood risk factor contributes very little to the return variation.

The second row of figure A2.1 reports the graphs for the size-sorted portfolios. Again, R-squared varies over the sample. For the portfolio based on the largest banks, market risk has the largest explanatory power over the time frame under consideration, followed by the value risk factor. Flood risk is irrelevant throughout. In the case of the portfolio of small banks, the exposure of the different factors is divided more equally. Even though market risk still contributes an important fraction of the variance, so does flood risk, size, and value. For some periods, even credit risk is an important contributor. Exposure to flood risk increases until 2015 before it almost disappears. The finding that the flood factor is more important for smaller banks is in line with the previous findings. Larger banks are active in a wider set of counties compared to smaller banks and can use their internal capital markets to redistribute funds to offset shocks. Simultaneously, they manage to diversify their exposure to single counties with large flood risk, while a local bank active in a single county at risk may not have this possibility. The two figures are supportive evidence for this hypothesis. The explanation is that overall larger banks are more active in securitization, and manage to reduce their exposure to the different types of risk. Market risk in their case proxies undiversifiable systemic risk. Hence, the rationale for the observed

[17] For further information, I refer the reader to the original paper by Klein and Chow (2013)

differences between the exposures of large and small banks is the same in the case of flood risk, as in the case of the remaining risk factors.

Finally, I split the sample into highly levered and low levered firms. Market, value, and size are important risk factors for the lowly capitalized bank sample. The exposure to flood risk does not matter too much. This finding might be explained by the findings in Rehbein and Ongena (2020). Levered banks are less able to raise additional funds, and thus can benefit less from increased loan demand following disasters.

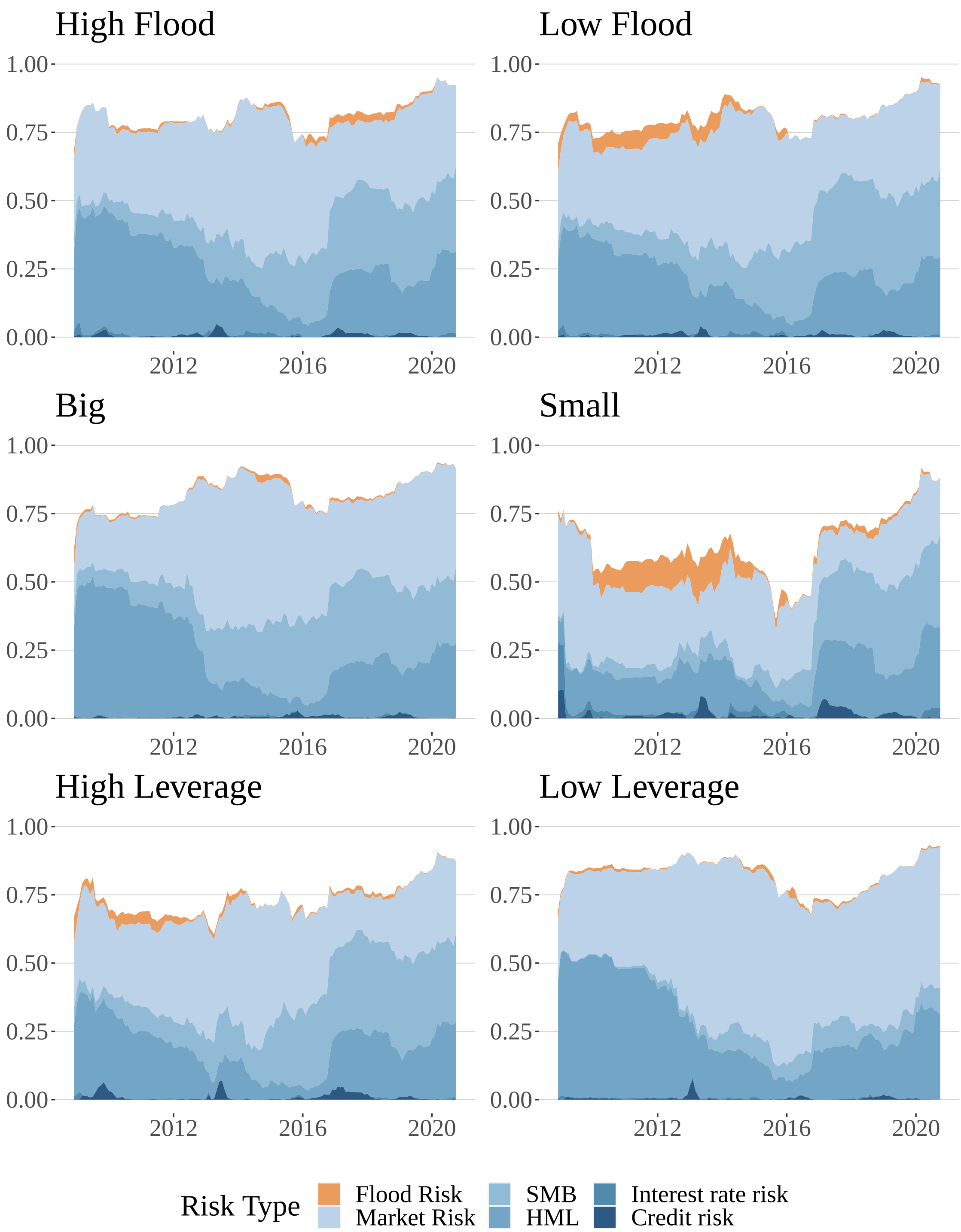


Figure A2.1: Variance Decomposition. Rolling variance decompositions for US bank portfolios. This figure shows variance decompositions for portfolios of US banks depending on bank characteristics. In the first row, the graphs plot the variance for the portfolio divided along their flood risk (above and below median); in the second row, portfolios are divided along market capitalization; third, the graphs use median leverage to split banks into two portfolios. The democratic variance decompositions are based on a rolling window of 48 months. All figures are presented in their scaled form.

A3. Principal Component Analysis

In section 4, I follow Fama and French (1993) sorting approach to create a flood risk factor: I sort banks on their flood risk measure and create a flood risk factor by subtracting the return of the lowest quartile portfolio from the highest quartile portfolio. The results so far have been derived using this approach. Further, I had shown the explaining power of common variation of the flood risk factor using a variance decomposition introduced by Klein and Chow (2013). In this section, I will present an alternative approach using Gandhi and Lustig (2015). The key assumption is that bank returns exhibit common variation. In this second approach, I use a Principal Component Analysis to study this variation and create the flood risk factor. Table A3.1 reports the loadings on the two first principal components from the four flood risk sorted portfolios. Q1 is the portfolio formed with the lowest quartile exposure, while Q4 uses the returns from the highest exposed banks. The second principal component in columns (2) and (4) have loadings that (almost) monotonically depend on the flood risk measure. Hence the covariance between sorted portfolio returns and flood risk can explain the pattern in sorted returns.

Table A3.1:
Principal Components of Flood Risk Sorted Bank Stock Returns

This table presents the loadings for the first and second principal components from the residuals of the four flood risk sorted portfolios after regressing the portfolio returns on the three Fama-French stock factors and the two bond factors from Gandhi and Lustig (2015). Standard errors are computed by bootstrapping the data 10000 times. The original data is bootstrapped and the procedure is applied to each bootstrapped sample. Columns (1) and (2) report the results for value-weighted portfolio returns, while columns (3) and (4) are generated using equal-weighted portfolios. The last row indicated the percentage of variation explained by the principal components.

		Value-Weighted		Equal-Weighted	
Portfolio		PC1	PC2	PC1	PC2
		(1)	(2)	(3)	(4)
Q1	Loading	0.35	0.94	0.48	0.83
	Std Dev	(0.06)	(0.04)	(0.01)	(0.05)
Q2	Loading	0.53	-0.23	0.51	0.01
	Std Dev	(0.02)	(0.11)	(0)	(0.09)
Q3	Loading	0.54	-0.16	0.5	-0.39
	Std Dev	(0.02)	(0.11)	(0)	(0.12)
Q4	Loading	0.56	-0.21	0.51	-0.41
	Std Dev	(0.01)	(0.09)	(0)	(0.09)
Variation		63.07%	19.78%	87.15%	6.71%

A3.1. Constructing the PC Loadings

The loadings from the principal component analysis reported in Table A3.1 are extracted from the residuals of the time-series regression of each flood risk sorted portfolio on the three Fama and French (1993) equity factors and the two bond factors from Gandhi and Lustig (2015). The first two principal components explain between 80% and 95% of the residual variation over the entire sample. The first component explains the major share, but also the second principal component explains almost 20% of the variation as shown in the last row of the table. The first two columns show results for value-weighted portfolio and the last two columns reports the results using equal-weighted portfolios. The numbers in parenthesis are standard errors generated by bootstrapping 10000 samples from the original flood risk sorted portfolio returns. The two sets of results are similar, but a bit more striking using equal-weighted portfolios. I will provide results for both weighing methods.

The first principal component can be viewed as an aggregated factor for the bank sector. The loadings are relatively constant for all portfolio types and across weighing methods. The second principal component loads positively on the portfolio of low-risk banks and negatively on the portfolio of high-risk banks. In the case of the equal-weighted portfolio, the loading decreases monotonically from the portfolio of lowest risk banks to the portfolio of highest risk banks. For the value-weighted portfolio, the result almost holds, except for the loading on the second quartile portfolio. The second principal component can be viewed as a potential candidate for the flood risk factor as the loading catch the pattern in risk I want to capture.

The loadings are used to construct the flood risk factor for this second approach. As an initial step, I rescale the loadings so that they sum up to 0 to have the same zero-cost portfolio as in the first approach. Next, still following Gandhi and Lustig (2015), I multiply the matrix of time-series return of the four flood risk sorted portfolios with the vector of (rescaled) loadings of the second principal components to obtain the new flood risk factor. Specifically this results in $R[PC2]_t = \boldsymbol{\hat{\lambda}_2 R_t}$. The factor is equal to the portfolio returns weighted by the rescaled second principal component ($\boldsymbol{\hat{\lambda}}_2$. As opposed to before, the new factor is long in low-risk banks and short in high-risk banks. Using this new flood risk factor, I run time-series regressions of the returns on the flood risk sorted portfolio on the flood risk factor $R[PC2]_t$ and controlling for the three equity and two bonds factors:

$$r_t^i - r_t^f = \alpha^i + \beta_{PC}^i R[PC2]_t + \boldsymbol{\beta}^{i\prime} \mathbf{F}_t + \epsilon_t^i \tag{A3.1}$$

The results from this regression for value-weighted and equal-weighted portfolios are reported in Panel A and Panel B of Table A3.2 respectively. Compared to the results from Table 7, we do not observe any trends in the alpha along the quartiles. This is further underlined by the insignificant alpha on the High-Low portfolio regression reported in column (5). Furthermore, most of the alphas are not statistically significant, suggesting that there is no discernable pattern in the portfolio return.

A3.2. Time-Series Dynamics

Next, similar to Figure A2.1 from the variance decomposition, I use the above method in a 72-month rolling window approach and plot the loadings of the second principal component for the four flood risk sorted portfolios and the proportion of the variance explained by the first two principal components. Figure A3.1 plots the series for the exposure-weighted portfolios. The top figure plots the time series of the loadings. We see that the monotonic trend in loading holds up until around 2015. From 2015 onwards, the pattern becomes more erratic. This pattern is observed throughout the paper: the significant alpha for the High-Low portfolio is only significant in the sample from 2004 to 2015; in the variance decomposition, the share explained by the flood risk factor is always small but vanishes after 2015. While the drop is not as sharp, the proportion of the variance explained by the second principal component also decreases a lot over the rolling-window sample as seen in Figure A3.1b. Now this result might be driven by short-term variations. Therefore I run the same analysis but using an expanding window setting. I start with a sample of 72-months and add one month at a time. The weights are reported in the top plots of Figure A3.2. Due to the increasing window-setting, the results are not as clear as in the rolling window-setting. Nevertheless, the plots suggest that the second principal component explains even less of the difference in flood risk sorted portfolio over time. This is evidence that flood risk predicted poor stock performance for high-risk banks in the early part of the sample, but the predictive power decreased. Although the results do not show a reversal of the weights (yet).

Table A3.2:
Flood Risk-Adjusted Returns on Flood Risk Sorted Portfolios

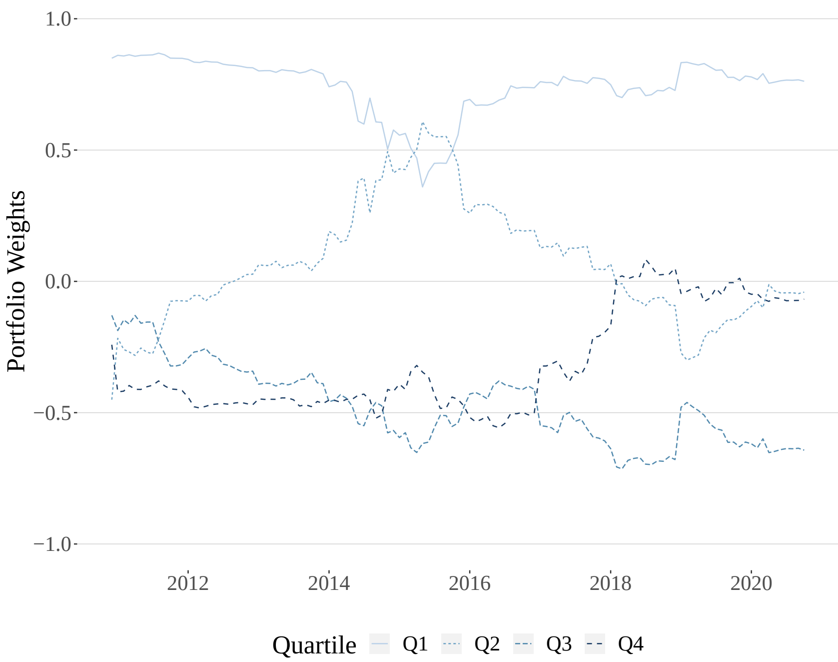
This table presents estimates from OLS regression of monthly equal-weighted excess returns on each Flood Risk Exposure-sorted portfolio of the bank on holding companies on the three Fama and French (1993) stock factors, two bond risk factors from Gandhi and Lustig (2015) and the second principal component weighted returns. Market, SMB, and HML are the three Fama-French stock factors: market, small minus big, and high minus low, respectively. CRG is the excess return on an index of investment-grade corporate bonds, while LTG is the excess return on an index of long-term government bonds. R[PC2] is the time-series of the returns of the four flood-sorted portfolios weighed by the rescaled weights from the principal component analysis w_t^i. The weights are scaled, to sum up to zero. The sample runs from 2004 to 2019. Standard errors are Newey-West adjusted with three lags. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Value-Weighted

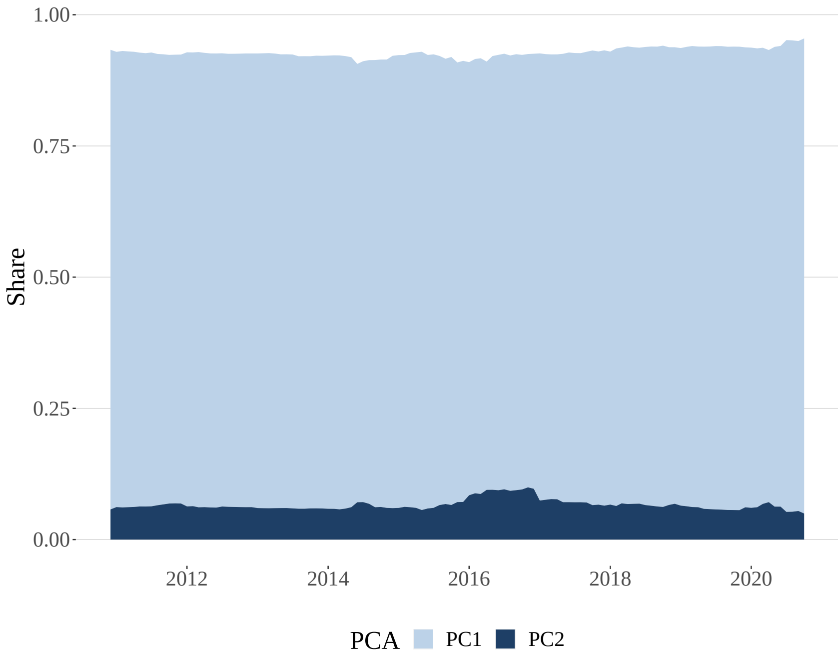
	Flood Risk Sorted Portfolios				
	Q1	Q2	Q3	Q4	HL
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.376**	0.575**	0.207	0.303	-0.073
	(2.02)	(2.36)	(0.956)	(1.54)	(-0.785)
R[PC2]	0.361***	-0.319***	-0.322***	-0.280***	-0.641***
	(6.56)	(-4.89)	(-5.02)	(-5.26)	(-30.0)
Factors Controls	YES	YES	YES	YES	YES
Obs.	179	179	179	179	179
R^2	0.824	0.753	0.809	0.839	0.888

Panel B: Exposure-Weighted

	Flood Risk Sorted Portfolios				
	Q1	Q2	Q3	Q4	HL
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.168	0.124	0.177	0.159	-0.009
	(0.724)	(0.518)	(0.802)	(0.641)	(-0.223)
R[PC2]	0.618***	0.113	-0.080	-0.098	-0.716***
	(5.80)	(1.28)	(-0.739)	(-0.894)	(-32.9)
Factors Controls	YES	YES	YES	YES	YES
Obs.	179	179	179	179	179
R^2	0.774	0.746	0.792	0.765	0.924

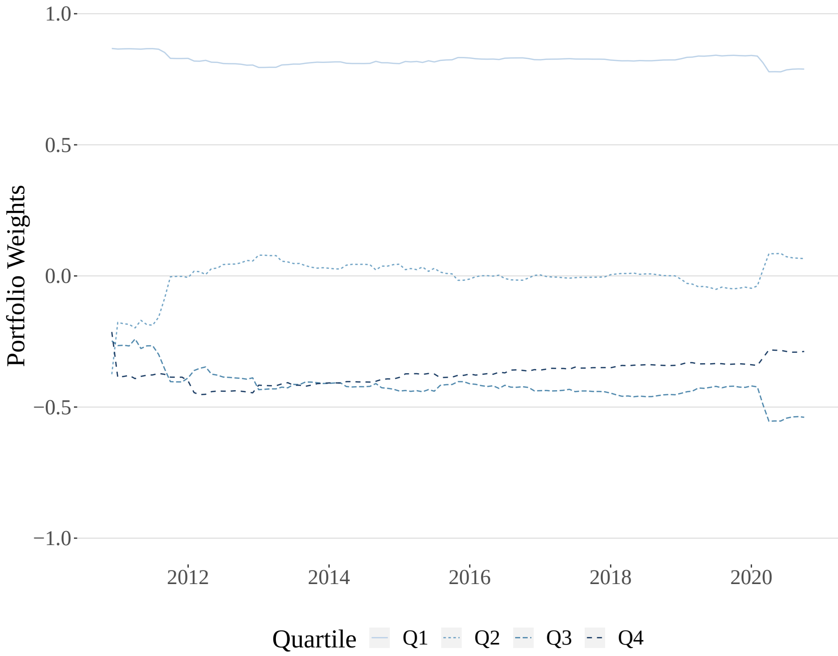


a) PCA Weights

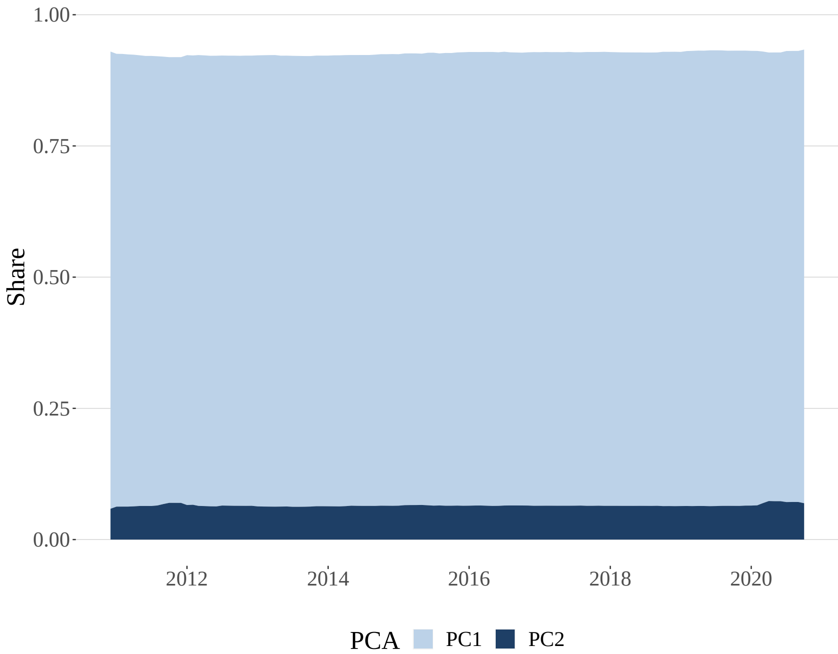


b) Variation in Returns

Figure A3.1: Expanding Window PCA. The top figure plots the loadings of the second principal component for the four flood risk sorted portfolios. The principal components have been extracted in a rolling window of 6 years (72 observations) starting in 2004. The bottom figure plots the proportion of the variance explained by the first two principal components. Portfolio returns are value-weighted. The full sample runs from January 2004 to December 2019.



a) PCA Weights



b) Variation in Returns

Figure A3.2: Expanding Window PCA. The top figure plots the loadings of the second principal component for the four flood risk sorted portfolios. The principal components have been extracted in a rolling window of 6 years (72 observations) starting in 2004. The bottom figure plots the proportion of the variance explained by the first two principal components. Portfolio returns are value-weighted. The full sample runs from January 2004 to December 2019.