Is Flood Risk Priced in Bank Returns?

Valentin Schubert*

Job Market Paper
This version: August 4, 2022

ABSTRACT

Policymakers are worried that markets are not paying enough attention to climate change risks to financial stability. Focusing on the banking sector and floods, I create a novel bank-level flood risk exposure measure based on mortgage lending data. I find that, following flood disasters, the profitability and capital ratios of affected banks decrease. However, in the cross-section of returns, stocks of banks with high exposure to flood risk underperform. The return predictability holds for small and medium-sized banks. Controlling for past disaster shocks or removing disaster months cannot explain this flood risk discount. The underperformance persists even when adjusting for investors' climate change concerns. The results suggest that systemic banks have little exposure to flood risk but policymakers' worry may be warranted for smaller institutions.

Keywords: Banks, stock returns, climate change
JEL classification: E44, G21, G12, Q54

*Department of Finance, Stockholm School of Economics. I would particularly like to thank my advisors Mariassunta Giannetti, Adrien d'Avernas, and Marcus Opp for helpful comments and suggestions, as well as Alvin Chen, Riccardo Sabbatucci, Robin Tietz, my discussants Ivan Ivanov, Yingjie Qi, Tamas Vadasz, and Martin Gustavsson, and seminar participants at the AREUEA Annual Meeting in Washington, the IMF RESMF, the 5th Benelux Banking Research Day, the Nordic Finance Network Ph.D. Workshop, the 10th Swedish National Ph.D. Workshop, the SSE/SHoF Ph.D. Brown Bag, and the 2021 meeting of the World Finance & Banking Symposium. All errors are my own. For any questions, please contact me at valentin.schubert@phdstudent.hhs.se

In the United States, weather disasters have caused over \$650 billion in property damages since 2010. The number of yearly billion-dollar disasters has more than quadrupled since the turn of the millennium (NOAA). Worldwide climate change is affecting the intensity and frequency of hazards. The widespread consensus is that without drastic measures, costs from climate change-related disasters are going to further increase over the next decades (Pachauri and Mayer, 2015). Policymakers are increasingly worried that local destructions could have severely negative effects on financial stability. In particular, regulators are concerned that markets do not pay enough attention to the risks and under-react to them (e.g., Carney, 2015; Lagarde, 2021). However, little research on the topic of physical risks from future climate hazards to the financial system has been conducted up to this point.

In this paper, I assess whether climate risks are priced in bank stocks. The analysis focuses on physical risks from climate change, specifically flood risk I exploit the regional variation in exposure of US domestic banks to local flood probabilities to examine how investors assess physical risks from climate change for the banking sector and their importance for the financial system's stability. Using a novel regional exposure measure based on mortgage lending activity matched to a flood probability measure for the continental United States, I find that banks with high exposure to flood risks underperform compared to non-exposed banks. This result implies a risk exposure discount and is puzzling in light of the risk under investigation. I identify small banks as driving most of the negative predictability. The effect is sizeable. A one-standard-deviation increase in the flood risk exposure is linked to a 20 bps lower average monthly excess return in the full sample or 30 bps for the sample of small banks. This translates into 2.4 and 3.6 percentage points lower annualized returns.

I hypothesize that banks are exposed to flood risk through the local residential real estate market. As a first contribution, I show that the real estate market transmits the costs from flood disasters to the banking sector. To this end, I construct a regional exposure measure at the bank holding company level using mortgage data from the Home Mortgage Disclosure Act (HMDA). The bank-level exposure measure allows me to assign the costs from floods to the different banks. I find evidence that floods significantly decrease bank profitability and increase leverage ratios. The effect lasts up to three quarters. Further, small and large banks are equally affected. For banks that specialize in mortgage lending, non-performing loans and mortgage charge-offs are also significantly higher for several quarters after major flood disasters. This analysis builds on previous papers (e.g., Blickle, Hamerling, and Morgan, 2021), but focuses on an additional exposure dimension. Previous papers have used branch location to identify exposed and non-exposed banks, but a bank is exposed to a much larger number of counties through its lending behavior. I show that when only focusing on branch locations, one wrongly concludes that disasters have no significant effect on profitability.

I provide evidence of the mortgage channel by separately looking at the effect of floods on mortgage delinquencies and the effect of delinquencies on bank performance. I show that residential mortgage foreclosures and delinquencies increase significantly after major weather hazards and, that periods of increased foreclosures are negatively linked to bank performance. Given the projected increase in storm intensity and sea levels, the mortgage exposure channel is likely going to gain importance.

Based on these results, I combine the regional exposure to county-level flood probabilities provided by the First Street Foundation to compute a bank-level flood risk exposure. I find a negative correlation between excess return and the bank-level flood risk exposure, 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 has been shown in other papers (e.g., Acharya, Johnson, Sundaresan, and Tomunen, 2022; Faccini, Matin, and Skiadopoulos, 2021; Hong, Li, and Xu, 2019). Further, I find that the result is mostly driven by banks in the top quartile of the flood risk distribution. The underperformance is mainly coming from the sample of small banks. While these are banks with smaller balance sheets, they are not only active in a single county or even state but are active across a number of borders, which renews the importance of capturing the full exposure using a bank's balance sheet information. In light of the earlier results that flood disasters are linked to lower profitability and higher non-performing loans, 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. I test whether the underperformance can be explained by flood disasters realizing. Counties with a high flood probability are highly correlated with counties experiencing flood disasters over the sample. Hence, the bank-level flood risk exposure could be picking up these disaster realizations. I perform a series of tests to rule out this potential problem. Using the property damage estimates, I find that the measured underperformance persists when controlling for past disasters. I also identify the negative relation using disaster-adjusted returns. Further, the flood discount prevails in a sample that removes periods with major floods and storms. Even when restricting the sample to banks with zero exposure to flood damages, the underperformance remains. The magnitudes are slightly smaller suggesting that a part can be explained by past disasters, but a significant underperformance remains.

The period from 2004 to 2020 also coincides with an important change in the assessment of climate change-related risks from the perspective of investors and the public in general. Recent literature has found that this transition period can explain differences in expected and realized returns for stocks of climate risks exposed firms (e.g., Pastor, Stambaugh, and Taylor, 2021). As investors' preferences for assets less exposed to climate risks increase, prices of these can outperform the 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. Using climate change attention data from Google and (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022), I find that climate change concerns are also linked to lower excess returns but they cannot explain the negative coefficient on the flood risk exposure.

While the main flood risk measure is based on flood probability by 2050, the main result is robust to using alternative measures such as county-level average risk scores or using 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 is evidence that the finding is not driven by outliers in the data. Furthermore, the results persist when controlling for differences in the local flood insurance. Using data from FEMA's National Flood Insurance Program (NFIP) covering 95% of the flood insurance activity in the United States, I find that results depend on the local insurance penetration: banks exposed to flood risk in counties with a high flood insurance take-up underperform less. Controlling for state-level changes in GDP, unemployment rate, and inflation I rule out that the flood risk exposure simply 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 including headquarter fixed effects does not change the results.

In a second step, using my bank-level flood risk measure, I sort banks in quartiles and compute a portfolio that goes long in the high flood risk portfolio and short in the lowest flood risk quartile. For the full sample, the portfolio underperforms by 43 basis points (bps) per month. This increases to 77 bps if I restrict the sample to small banks. This translates to over 9% annualized. Next, I create a trade-able flood risk factor by subtracting the portfolio returns of the bottom 25% of banks from the portfolio returns of the top 75% of banks as measured by their flood risk measure. Rebalancing yearly using the flood risk exposure, I find that the factor produces negative returns on average. The exposure-weighted cumulative portfolio return exhibits some time variation but follows a downward trend. Overall the factor lost around 50% from 2004 to 2020 in the full sample and 80% for the small bank sample. The flood factor has an alpha of -23 bps in the full sample (or -56 bps for small banks). Controlling for the Carhart (1997) four factors does not alter the results. When regressing bank-level excess returns on the flood factor, I find a positive and statistically significant beta, which suggests that the flood risk factor explains shared variation in the returns of bank stocks. The result holds when controlling for the bank literature factors either by adding them as controls or when computing abnormal returns first. Using a variance decomposition method introduced by Klein and Chow (2013), I show that flood risk represents a negligible systematic risk for the banking sector. Using a rolling window variance decomposition approach, I find that flood risk exposure varies over time and across subsamples of bank holding companies, but never represents a major risk source.

This paper is most closely related to the literature on climate risks and financial markets. In a cross-country analysis, Hong, Li, and Xu (2019) find that stock markets under-react to the long-term risk of drought. Similarly, Duan, Li, and Wen (2021) find that investors under-react to carbon risk using corporate bond returns, while on the other hand, Bolton and Kacperczyk (2021) find that stock returns of firms with a higher level of carbon dioxide emissions are higher. Hsu, Li, and Tsou (2021) find evidence of a pollution premium by sorting firms along their carbon emissions. These papers focus on non-financial corporates and industries, while I specifically study the implication of physical risks from climate change to the financial sector and stability. Using Google search trends, Choi, Gao, and Jiang (2020) show that stocks of carbon-intensive firms underperform when temperatures are abnormally high. Acharya, Johnson, Sundaresan, and Tomunen (2022) find that exposure to heat stress commends higher returns on municipal and corporate bonds as well as in the cross-section of stock returns. Pástor, Stambaugh, and Taylor (2021) unify the findings from these two strands and 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. Investor attention to climate change risk is a key part of this analysis but is not explicitly modeled.

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 the lending in affected areas following a 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 effect on the bank's performance is also less clear. 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 decrease and non-performing loans (NPL) increase. I provide evidence that flood disasters have a negative impact on bank performance. I show the importance of correctly capturing a bank's exposure to shocks. While papers focused on the US use branch location to proxy for exposure, 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 headquarters cannot capture the link.

The paper uses results from the literature studying the effect of weather hazards on real estate markets. Using property level data matched to sea level rise, Murfin and Spiegel (2020) finds no effect on real estate prices. Similarly, Keys and Mulder (2020) do not find that property at higher risk of flooding sold at a discount in Florida for most of their sample. Gibson and Mullins (2020) find insignificant results for real estate in New York.

Some papers find that houses at risk of flooding trade sell at a lower price, but only for specific types of households (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 captured by 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.

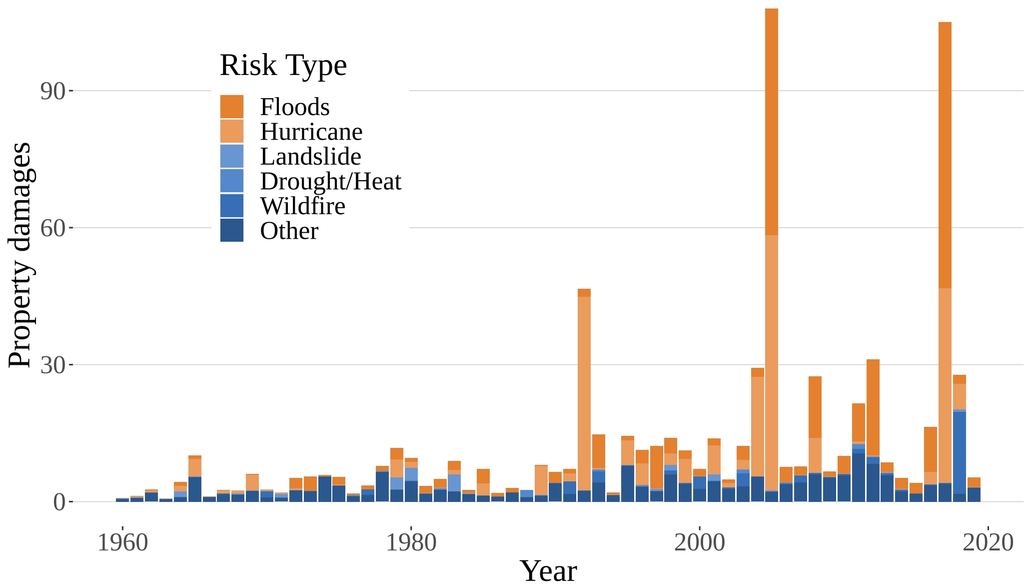
The remainder of the paper is organized as follows. Section I highlights the main channel and develops the key predictions to be tested. Section II describes the data and introduces the main explanatory variables. Section III documents the negative effect of flood disasters on mortgage and bank performance. Section IV asks if future flood risk is priced in bank stock returns. Section V discusses the role of flood insurance and investor attention to climate change. Section VI concludes.

I. Flood Risk Channel and Empirical Predictions

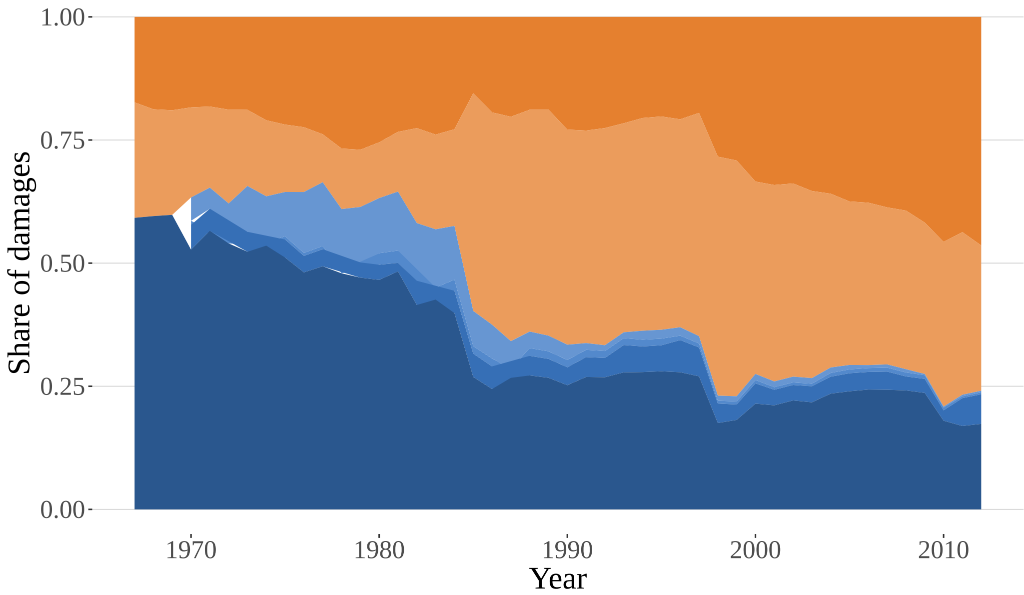
In this section, I describe the channels through which floods affect bank performance. As pointed out by the ECB (2019), with increases in frequency and severity of climate disasters, the risk of abrupt value losses of assets in climate risk-sensitive geographical areas increases. As real estate is notoriously linked to its geographic location, this can lead to the erosion of collateral and asset values for a large number of financial institutions active in this region.

I focus on floods and hurricanes for the simple reason that measured by property damages, they represent by far the costliest disasters in the United States. Figure 1 plots the estimated damages from natural disasters in the United States. In the last ten years, the amount of damages from floods and hurricanes has strongly increased. Additionally, as shown in Figure 1b they account for over three-quarters of the estimated property damages caused by natural disasters. A second reason is that their frequency and intensity are projected to further increase in the next decades.

So first, rising flood prediction risk may eventually lead to an increasing number of household delinquencies and defaults, which ultimately affects banks' income and profitability. Further exacerbating the problem may be balance sheet write-offs of mortgage-backed securities. And second, sudden decreases in the value of collateral can lead to sharp readjustments in household behaviors such as borrowing and consumption (Mian and Sufi, 2011), which may directly affect a bank's economic performance in the region. Given the lack of evidence that banks account for this risk directly (e.g., Garbarino and Guin, 2021), this may pose an increasingly important risk to banks that should ultimately be accounted



(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.

for by investors.

The first prediction considers the entire channel in a single instance. It stipulates that severe flood hazards have a direct negative impact on exposed banks. I test this prediction by looking at banks' balance sheet performance following past flood disasters. The hypothesized channel works mainly through the residential real estate market. It assumes that the market is significantly negatively affected by flood hazards. Given its strong local ties, the real estate market is exposed to concentrated risk. Major storms and floods are exactly a type of risk that affect a large number of properties simultaneously. The first prediction is, therefore:

PREDICTION 1: *Flood hazards are negatively correlated with bank performance.*

Next, I analyze the channel in two parts, because by looking at past flood disasters, the risk of future floods is underestimated given the expected increases in extreme weather events. The second prediction specifies that floods increase local household delinquencies. This prediction is tested using local mortgage performance aggregates after major flood episodes.

PREDICTION 2: *Flood hazards are positively correlated with residential mortgage delinquencies and foreclosures.*

For the channel to exist, increased delinquencies and foreclosures need to have a negative impact on bank performance. This is the third prediction.

PREDICTION 3: *Residential mortgage performance is positively correlated with bank performance.*

Finally, if the risk of flood represents a systematic risk and markets are efficient, then the risk of flood should be priced in bank stock returns. This holds true even if prediction 1 were to not hold, but prediction 2 and 3 are satisfied. As future disasters are projected to be more intense and more frequent, inferring damages and reactions from past disasters lead to conclusions that are too optimistic. I test this prediction using flood risk maps and bank stock returns.

PREDICTION 4: *Flood risk exposure forecasts higher expected bank stock returns.*

II. Data and Summary Statistics

The paper's empirical analyses can be divided into two broad sections. The first section focuses on past flood disasters and measures of mortgage and bank performance, while the second part centers around the risk of future flooding. To do so, I require estimates of property damages from past floods, as well as geographic probabilities of flooding that I combine with a bank-level county exposure measure based on mortgage lending data to create novel flood risk exposure. The final dataset focuses on banks active in the United States during the years 2004 to 2020. In this section, I describe the different data sources and introduce the key explanatory variables used in Section III and IV. On average the final data contains information from 400 bank holding companies (BHC) covering 2004 to 2020. The analysis on the subsidiary level includes data from 4300 banks (that includes non-listed institutions).

A. Bank-Level County Exposure

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). Depository institutions that are federally insured or regulated with total assets exceeding a time-varying threshold defined by the Consumer Financial Protection Bureau (CFPB) that originated at least one home purchase loan or the refinancing of a home purchase loan with an office in a metropolitan statistical area are required to report.[1] As the paper mostly focuses on publicly listed banks, which typically are large, the minimum threshold is not an issue. It is mortgage application-level data and includes information on the mortgage, such as amount, geographic location of the home, type (purchase, refinancing, etc.), and year of application. Importantly, the data contains information about the status of the application (accepted, originated, declined, etc.). In the context of this study, I restrict the data to 1-4 family home purchase loans that originated. Furthermore, I drop observations with missing locations and no information on owner-occupancy. The main focus will lie on mortgage loans the emitting institution retains on its balance sheet. However, the remaining home purchase loans are divided along their purchaser types: i) sold to another financial institution, ii) sold to a GSE, or iii) securitized. The home loans are then aggregated by their type to the institution-year-county level with aggregate information on originated loan amounts retained on its balance sheet, sold off to other financial institutions, securitized, or sold to the two GSEs. The sample is restricted to the years 2004 to 2020. The data is linked to damages estimates and the flood probabilities using the 5-digit FIPS (county) code.

B. Property Damages Data

Flood hazard-related property damage estimates come from the Spatial Hazard Event and Losses Database for the United States (SHELDUS) maintained by the University of Arizona.[2]It is available at the County-Month-Hazard Type level covering the US. Hazard types include floods, hurricanes, thunderstorms, wildfires, and earthquakes amongst others. The database includes information on the location (county), property losses, crop losses,

[1] In 2018 the minimum threshold was set at $45 million and is typically adjusted over time according to inflation.

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

injuries, and fatalities. The data are a combination of different publicly available data sources. Estimates are derived from reports from insurers and local weather stations.

C. Flood Risk Maps

To implement the research design focused on flood risk, 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 (FSF) in partnership with researchers at George Mason University, Fathom Global, and the Rhodium Group.[3] I use this alternative over the more widely used flood maps produced by FEMA, because, according to the FSF, the number of properties with a substantial risk of flooding is approximately 70% higher than what is estimated by FEMA's maps. Therefore, the maps from FSF represent a better measure of the underlying flood probability of a county.

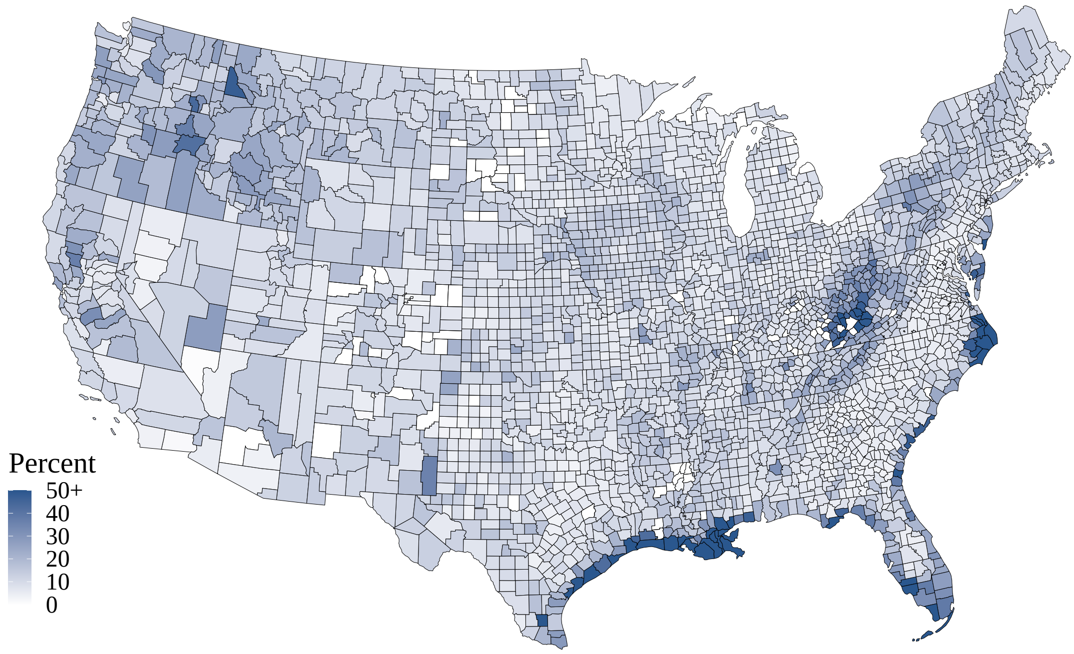


Figure 2. Flood Risk Map. This figure plots the county-level flood risk. The data comes from First Street Foundation and shows the number of properties with a 1% probability of flooding by 2050.

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

[3]Fathom Global specializes in modeling flood risk and originates from the University of Bristol Hydrology Research Group. Rhodium Group focuses on producing climate change-related data.

active in landlocked regions. Further, 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. To my knowledge, I am the first to link these flood maps to regional bank activity.

For this study, I use information aggregated at the county level. 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, but also counties in lower regions of the Northwest and counties in the Appalachian are projected to be of high risk.

D. Mortgage Performance Data

The mortgage performance data comes from two separate sources. First, information on foreclosures is from RealtyTrac, which is a large marketplace for foreclosure properties in the United States. I have access to data from 2004 to 2013. The data includes information on the location (county) and foreclosure date.

Second, I use Fannie Mae's Single-Family Loan Performance data for delinquency status. The data is a monthly performance file of all mortgages in Fannie Mae's possession. It includes information on the mortgage's original terms such as the amount and origination date, information on the borrower (income, credit score, debt-to-income), and information on delinquency status and potential costs to Fannie Mae. Location information is provided as the first three digits of the ZIP code (zip3). Delinquency status can be broken down into delinquency length: from 30 days to up to 180 days.

E. Bank Performance Data

For the analysis of bank performance following flood hazards using accounting information I use the Statistics on Depository Institutions database of the Federal Deposit Insurance Corporation (FDIC SDI). This data is filed quarterly and includes balance sheet and income data of all FDIC-insured U.S. banks. The main dependent variables of interest are Return on Assets, different capital ratios, and write-offs or non-performing loan ratios. Control variables such as total assets and the number of employees are also provided. The advantage of this data is that it allows me to cleanly merge to the HMDA data used for the county exposures. The sample spans from 2004 to 2020.

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

To match information from HMDA to CRSP, I require several linking tables provided by the Federal Reserve. I can match the FR Y-9C form to the HMDA filings in several steps. First, the filer ID from the HMDA filings (HMDA ID) is matched to information in FFIEC Call Reports for each filing year using a key provided by the Federal Reserve upon request.

In a second step, the FFIEC Call Reports' RSSD ID has to be matched to the BHC's RSSD ID using a 'Parent-Offspring' linking file. I proceed by aggregating the HMDA data to the BHC resulting in data at the BHC-county-year level. This panel can then be matched to the data from the FR Y-9C reports. Further, as stock returns are valid for the consolidated bank holding company, I use the FR Y-9C *Consolidated Report of Condition and Income* filed every quarter by U.S. BHC with the Federal Reserve for control variables. The data is very similar to the FDIC SDI but is reported on a consolidated basis, including both bank and nonbank subsidiaries owned by the BHC.

The FR Y-9C filings include detailed information about the balance sheet and income, as well as data on loan performance. In my analysis, I extract information on balance sheet size (total assets), funding structure (deposits, Tier 1 capital, equity), and non-performing loans. As I focus on real estate for my exposure measure, I also compute total residential real estate loans and commercial real estate loans on the consolidated balance sheet. I restrict the data to the quarters between 2004Q1 to 2020Q4.

F. Additional Data

I use data from the National Flood Insurance Program (NFIP) from FEMA. The data is available in two separate files. The first file includes information on policies and is available from 2009 to 2022. It includes information such as the coverage and premium of individual policies. An important feature of the insurance program is that the coverage is capped at $250'000 for residential properties. However, the private market for flood insurance is limited. The NFIP typically covers over 95% of all flood insurance policies in the United States. On average, the data includes around 4 million active policies with a total insured amount of $1 trillion. Building coverage equals roughly $750 billion, while around $250 billion in content is covered. The number of active policies as 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 as seen in Figure **??**.

G. Measuring Banks' Exposures to Floods

To test Prediction 1, 3, and 4, I need to aggregate county-level measures at the bank-level. I achieve this using a novel county exposure of each bank. The county exposure is 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 kept on the balance sheet. Equation 1 formalises this.

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

$Retained_{b,c,t}$ is the total amount of mortgages originated in county c and year y by bank b that bank b retains on its balance sheet.

For Prediction 1, I combine this county exposure with county-level property damage estimates from SHELDUS. Formally, I have:

$$Damage\ Exposure_{b,q} = \sum_{c} (County\ Exposure_{b,c,y} \times Property\ Damage_{c,q}). \tag{2}$$

The damage exposure can be viewed as a weighted average of the damages that occurred in quarter q. Similarly, for Prediction 3, I combine local mortgage performance data from Fannie Mae or RealtyTrac with my county exposure to create a bank-level measure.

$$Mortgage\ Performance\ Exposure_{b,q} = \sum_{c} (County\ Exposure_{b,c,y} \times Mortgage\ Performance_{c,q}), \tag{3}$$

where mortgage performance is either number of delinquencies, delinquency rate, or total foreclosures. The delinquency rate is calculated by dividing the total number of delinquencies by the occupied housing units retrieved from the US Census Bureau.

Finally, for Prediction 4, I create a bank-level flood risk exposure by weighing the share of properties at high probability of flood with the bank's county exposure defined in equation 1. Formally, I have equation 4

$$Flood\ Risk\ Exposure_{b,y} = \sum_{c} (County\ Exposure_{b,c,y} \times Flood\ Probability_{c}). \tag{4}$$

In robustness tests, I alternatively use the county-average risk measure and the share of properties at risk by 2035.

H. Summary Statistics

Table I reports the summary statistics and differences between banks with a high exposure to flood risk and banks with a low exposure to flood risk. 'High' risk banks are defined as banks within the top quartile sorted on the flood risk exposure in each year, while 'Low' are all other banks. Mortgage-based variables change at an annual frequency. Stock variables are based on monthly stock returns. And finally, balance sheet variables from the Call Reports are updated quarterly. As a sanity check, the two groups do differ significantly along the key measures of flood risk exposure. Depending on the measure at hand, high flood risk banks have up to 3 times more mortgages in high-risk counties compared to low-risk banks. From the table, it also becomes apparent that the two groups differ along some important variables. High-risk banks are active in fewer counties (and states) but do not originate significantly fewer mortgages nor do they retain fewer amounts. They are however smaller on average and therefore are more focused on mortgage lending. They also rely more on deposit funding. Importantly, on average, they do not differ in profitability (ROA), the share of non-performing loans, or leverage ratio. I will account for the observed differences by performing different subsample analyses in the later sections.

Table I
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 Flood Exposure		Low Flood Exposure				
	Mean	Obs	Mean	Obs	Difference	t-Statistic	Significance
Mortgage-based Variables							
Application Amount (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 Amount (Thsd)	519.7	1,721	516.4	5,157	3.3	0.1	
Average Retained Amount (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	***
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	***

Continued on next page

Table I – *Continued from previous page*

	Low Flood Exposure		High Flood Exposure				
	Mean	Obs	Mean	Obs	Difference	t-Statistic	Significance
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	***

III. The Effect of Flood Disasters

A. *Bank Performance following Flood Disasters*

The first empirical strategy involves regressing bank outcomes on the measure of exposure to flood damages introduced in Section II. Formally, I estimate the following equation:

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

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, I include 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 level. The model saturated with fixed effects allows me to evaluate whether bank outcomes are driven by the exposure to flood damages holding constant unobserved bank and aggregate market characteristics.

Panel A of Table II 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, flood disasters typically have a large left tail, hence a 10 standard deviation shock is plausible. In this scenario, returns on assets would see a 10% decrease, consistent with flood damages having a potentially important effect on bank performance.

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. In this paper, I argue that banks are exposed through their assets. An exposure measure to natural disasters should therefore reflect a bank's asset side as opposed to its liabilities. Furthermore, and more importantly, I argue that a bank's main exposure is through its mortgage loan exposure. Finally, banks

Table II
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

typically extend loans outside of their home counties. Hence focusing on physical bank location potentially omits important exposures. Panel B of Table II 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, I focus on deposit-weighted, while column (3) uses the county exposure using physical office locations. The coefficients of interest are insignificant in both cases. This suggests that only using physical locations as exposure omits an important share of the overall bank exposure.

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 experience higher damage levels. To rule out that this is driving my results, in column (1) of Panel B of Table II, I use total property damages divided by county-level total personal income as a damage measure. In this context, the coefficient is of similar magnitude as in the baseline results, suggesting that wealth differences are not driving the results. Going forward, the presented results will be based on the damage ratio exposure.

Next, I consider the implications at the consolidated bank level. The first set of results is based on data at the subsidiary level from the FDIC SDI database and includes banks not publicly traded. In the next step, and throughout the rest of the paper, the analysis is restricted to publicly traded bank holding companies. Focusing on this subsample of banks later allows me to talk about stock market reactions and expectations.

Table III reports the results from equation 5 for a set of balance sheet variables of bank holding companies. All regressions control for time-varying bank characteristics such as leverage, assets, loan ratio, and mortgage ratio. As previously, I include bank and time fixed effects, 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 II, suggesting that the effect is propagated at the bank holding company. Columns (2)-(3) focus on prudential capital requirements. The estimates in columns (2) and (3) 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. Both coefficients are statistically significant, with t-statistics below -2.56. This finding suggests that not banks not only have lower profits but experience losses on their equity. 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).

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

$$\textit{Z-score}_{bt} = \frac{roa_{bt} + equity_{bt}}{\sigma(roa_{bt})},$$

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, consistent with flood damages increasing the default likelihood of

Table III

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)		
Charge-Offs							0.369***	

Continued on next page

Table III – *Continued from previous page*

	ROA_{t+1}	$Leverage_{t+1}$	Capital $Ratio_{t+1}$	$SWFR_{t+1}$	$Z\text{-}Score_{t+1}$	NPL_{t+1}	Charge-$Offs_{t+1}$	Loan $Loss_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							(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

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. This is at least suggestive evidence that the performance of loans decreases following flood disasters.

B. *Effect Heterogeneity of Disaster Realizations*

Undoubtedly, there is significant heterogeneity in the effect of *Flood Damage Exposure* on performance variables. Small banks in the sample are probably less diversified and have more concentrated lending. Therefore a county-level flood disaster affects 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 IV 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 of the mortgage lending share and size, respectively.

Panel A of Table IV 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 coefficients on *Flood Damage Exposure* are significantly negative across the four specifications and range from -0.004 to -0.011, which represents no major differences among the different subsamples. The magnitude of the coefficient of the $High$ mortgage loan share is somewhat larger than for the *Low* sample, consistent with my prior. 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 smaller banks.

The baseline results from Table III implied an insignificant relation between flood damages and the loan performance variables. The results for the partitioning suggest that firms with a larger proportion of mortgages on their balance sheet react more strongly to an increase in flood damages. In particular, I find a statistically significant positive relation between *Flood Damage Exposure* and non-performing loans (column (1) in Panel B of Table IV) and mortgage loan charge-offs (column (1) in Panel C of Table IV). 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 for this subsample of banks with are insignificant in both cases (column (2) in Panel B and C of Table IV). Moreover, the coefficients suggest that this does not appear to be due to a lack of statistical power, as the coefficients are not only statistically insignificant but also smaller in magnitude.

Next, I partition the sample based on bank size (columns (3) and (4)). Specifically, I

Table IV

Examination of Heterogeneity in Bank Returns on Assets

This table partitions the results from Table III 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

split the sample above and below the median of the total assets.[4] Surprisingly, the results suggest that the effect is stronger for larger banks. The increase in the non-performing loan ratio after flood damages is concentrated in large banks. Specifically, I find no evidence that the sample of small banks incurs an increase in their non-performing loans. Finally, in Panel C, I find no difference between the two size-sorted samples. The relation between flood damages and loan charge-offs is insignificant in both samples. These findings suggest that, if anything, larger banks react more strongly to flood damages.

C. *Persistent Effects on Performance*

In the previous analysis, I focused on one-quarter ahead performance variables. Natural disasters, such as floods, might 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 second empirical strategy involves regressing bank outcomes in periods $t + h$ on the measure of exposure to flood damages introduced in Section II. Formally, I estimate the following equation:

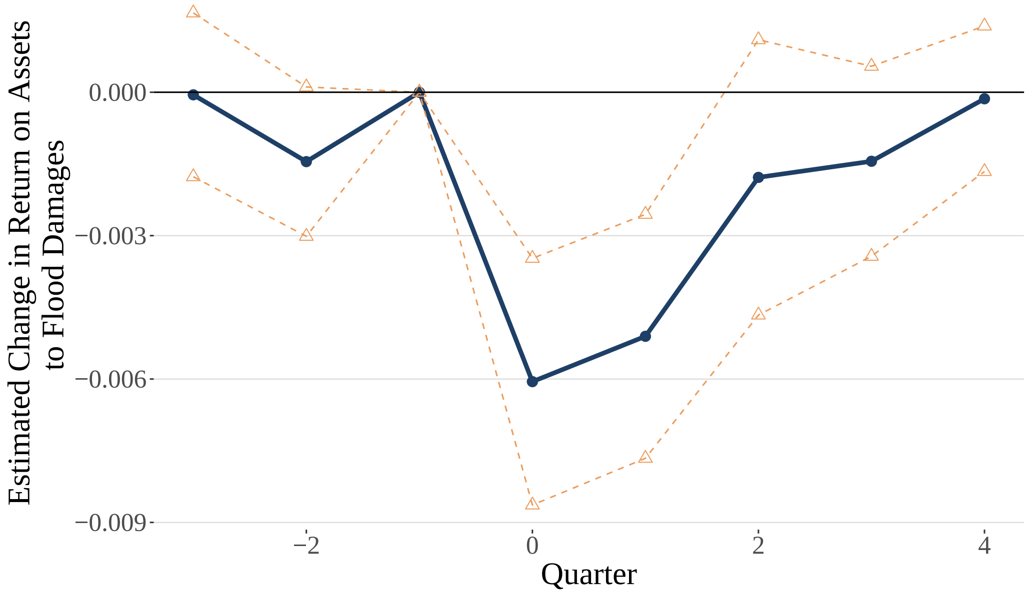
$$\begin{aligned} Y_{bt+h} = \beta_0 &+ \beta_1^h \textit{Flood Damage Exposure}_{bt-1} + \beta_2^h Y_{bt-1} + \beta_3^h \textit{Capital Ratio}_{bt-1} \\ &+ \beta_4^h \textit{log(Employees)}_{bt-1} + \beta_5^h \textit{log(Assets)}_{bt-1} \\ &+ \beta_6 ROA_{bt-1} + \boldsymbol{\gamma X} + \epsilon_{bt}^h,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

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 3. 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.

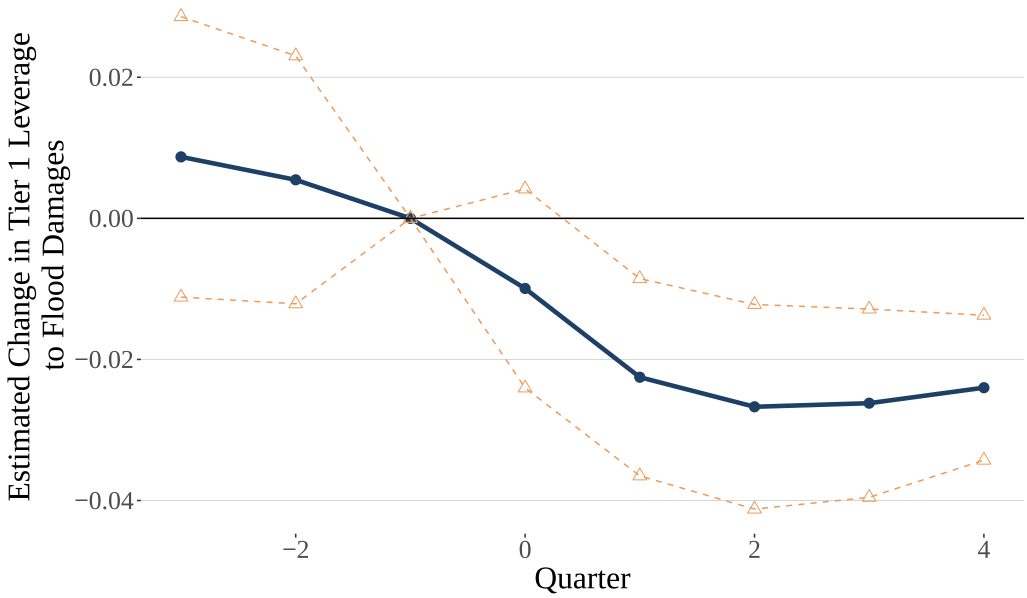
Figure 3a shows the long-run effect of flood damages on bank-level return on assets. The quarter 1 coefficient is the same as the coefficient in column (1) of Table II. The plot suggests that the drop in return on assets starts in the same quarter as the flood and tappers off over the next year, consistent with the effects of floods having longer-term consequences. The finding is echoed in Figure AII.IVb that plots the coefficient for e regression of Tier 1 leverage on flood damages. Following a flood, leverage decreases for three quarters before leveling off. Surprisingly in the one-year horizon, leverage remains significantly below its pre-flood level. This result emphasizes the long-lasting effects of a disaster. In both plots, the coefficients in the quarter before the floods are statistically insignificant.

Taken together, the evidence in Panel A and B of Figure 3 is consistent with banks experiencing significant losses from floods that require the bank to tap into its equity.

[4] The results are qualitatively similar if I partition at the third quartile (Results not reported).



(a) Return on Assets



(b) Tier 1 Leverage Ratio

Figure 3. 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. 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.

Figure 4 conducts a similar analysis using two mortgage performance variables as the outcome of interest. As seen in Section III.B, the effect on loan performance variables is only seen in a subsample of banks with a high share of mortgage loans. Therefore, Figure 4a plots the coefficient from regressing the non-performing loans ratio on flood damages for the banks with a high share of mortgages. Again, 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. Similarly, as shown in Figure 4b, loan charge-offs increase in the quarter following the shock and remain elevated for the next couple of quarters.

Taken together, the evidence Figure 3 and 4 is consistent with banks' balance sheets deteriorating significantly after flood disasters and that the effect manifests itself over a relatively long period.

D. Bank Stock Reaction to Hurricane Katrina

In the following subsection, I analyze the stock market reaction to disaster news. Specifically, I focus on the landfall of Hurricane Katrina on the Gulf Coast of the U.S. in August 2005. 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 become clear, markets should have priced the potential exposure to the damages.

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

$$AR_{bt} = R_{bt} - E[R_{bt}]. \tag{7}$$

The daily expected return is defined as

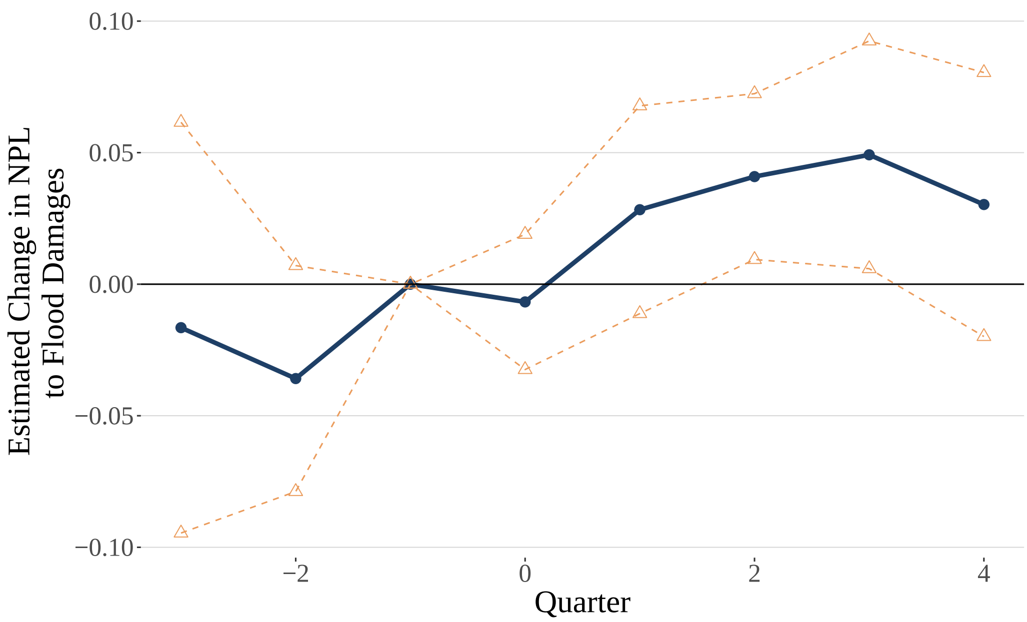
$$E[R_{bt}] = \hat{\alpha}_b + \hat{\boldsymbol{\beta}}_{\boldsymbol{b}}' \boldsymbol{F},$$

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:

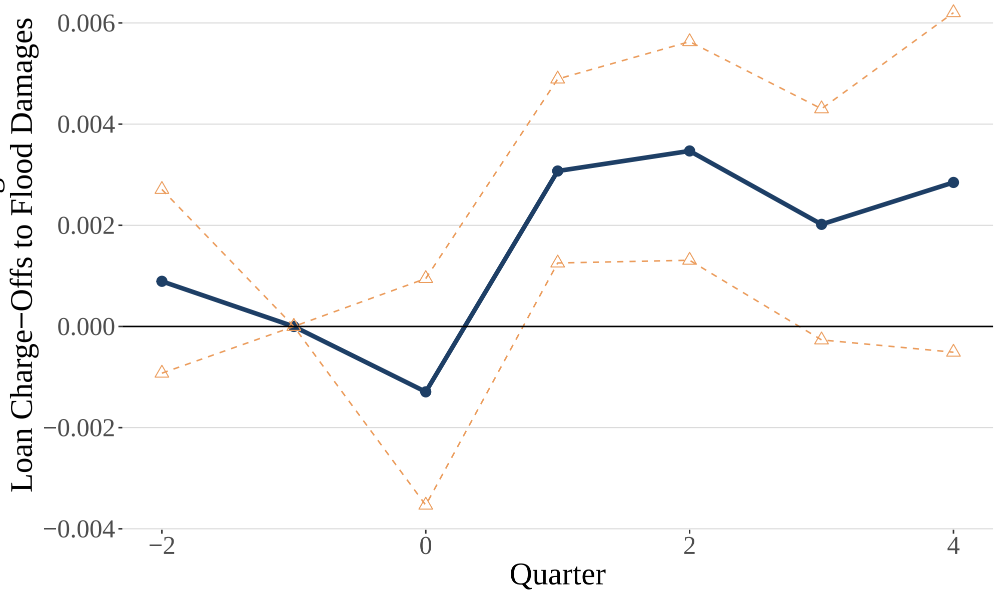
$$R_{bt} = \alpha_b + \boldsymbol{\beta}_{\boldsymbol{b}}' \boldsymbol{F} + \epsilon_{bt}.$$

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.[5] During the hurricane season of 2005, 135 of the 534 counties in the Gulf Coast

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



(a) Non-performing Loans



(b) Loan Charge-Offs

Figure 4. 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.

region were designated to be eligible for FEMA's disaster assistance. I classify a bank as affected by Hurricane Katrina if all its mortgage lending in the previous year was for properties located in a county eligible for individual and public disaster assistance (the orange region in Figure 5a). I classify the control group as 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.[6] These counties are shown in dark blue in Figure 5a. 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, I cleanly identify 19 banks only active in affected counties and 27 banks located in unaffected counties.

Next, I compute the value-weighted return of the portfolios consisting of affected and unaffected banks. Figure 5b plots the daily cumulative abnormal return of the two portfolios for the months July 2005 to October 2005.

Hurricane Katrina formed on August 24. In the days following, the intensity and trajectory of the storm became more and more apparent, leading to slightly negative abnormal returns. And as the storm made landfall on August 28, the CAR of affected banks dropped by over 10% in a matter of days. This is equal to a \$3bn loss in market capitalization of affected banks. Interestingly, abnormal returns remained negative for a considerable amount of time and the CAR never recovered over the sample.

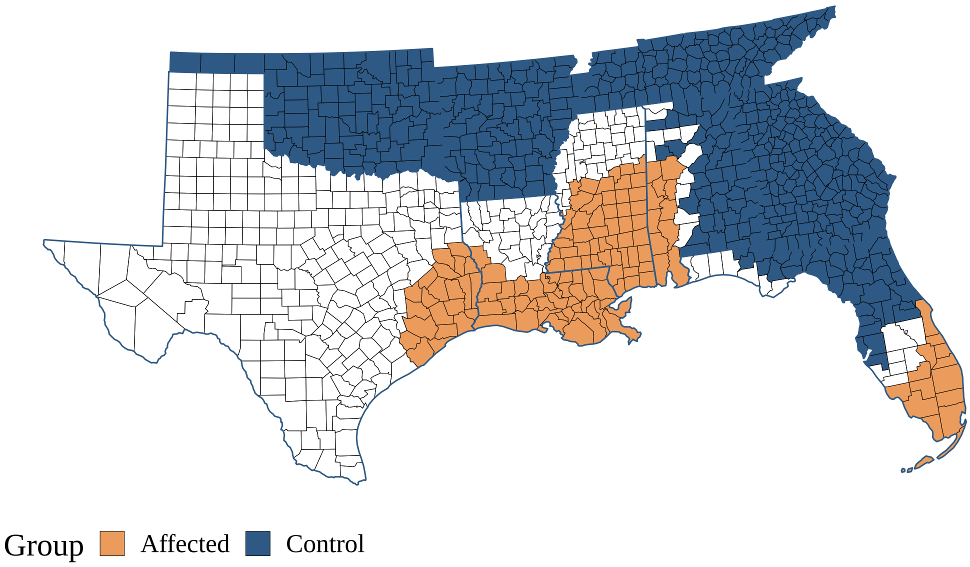
E. *The Role of Mortgage Market in Propagating Flood Disasters*

In this subsection, I provide evidence for the importance of exposure to the residential real estate sector for the transmission of flood disasters to bank performance. The empirical approach involves regressing county (or Zip) level mortgage performance ratios on flood damages. Formally, I estimate the following equation:

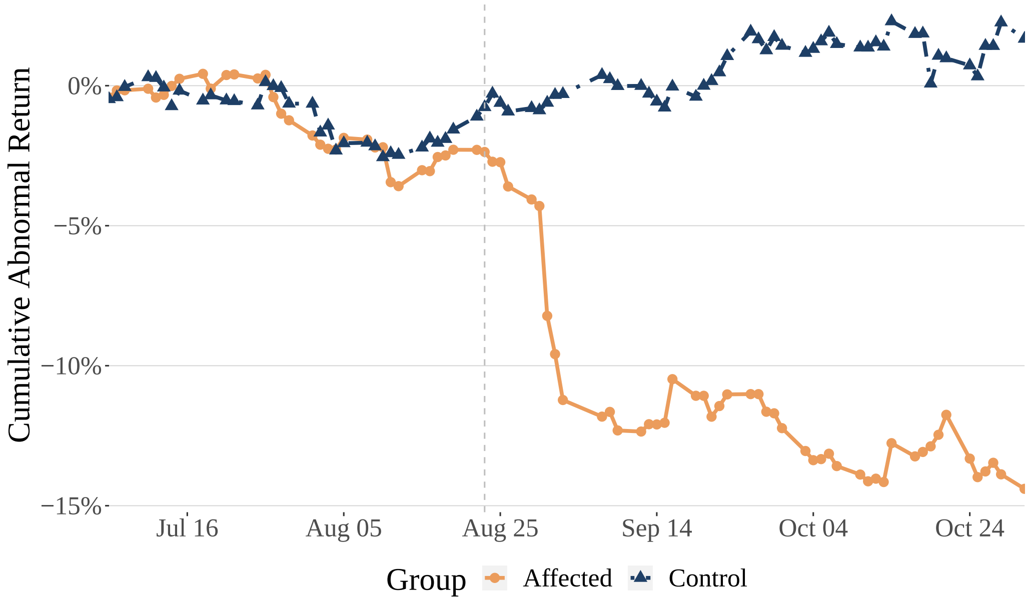
$$\begin{aligned} \mathrm{Y}_{ct+h} = \quad & \beta_0^h + \beta_1^h \mathit{Flood\ Damages}_{ct} \\ & + \beta_2^h Y_{ct-1} + \boldsymbol{\gamma} \boldsymbol{X} + \epsilon_{ct+k}, \end{aligned} \tag{8}$$

where Y_{ct} represents the outcome of interest, foreclosures, and delinquency ratio. The regression includes the lag Y. The main explanatory variable is *Flood Damages* constructed using property damage estimates at the county level and monthly frequency. To account for the difference between urban and rural areas, I compute a *Flood Damages* by dividing the county-level property damage estimates by the total personal income in a county. The data for personal income comes from the U.S. Census Bureau. Further, I include time (month) and county fixed effects, given by the vector of $\boldsymbol{X}$. The county fixed effects ensure that results are unlikely to be driven by unobserved county characteristics, while the time

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



(a) Affected Areas



(b) Cumulative Abnormal Return

Figure 5. 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).

fixed effects alleviate concerns that the results are driven by specific periods. Standard errors are clustered at the state level.

Figure 6a reports the coefficients β_1^h for $h = -3 : 7$ from regressing the county-level number of foreclosures on the flood damages. The solid blue line reports the point estimates, while the 95% confidence interval is the dashed orange line. The coefficients are insignificant for the periods prior to the shock (proxied by the property damages). Following the shock, the coefficient increases to 1 and remains at that level over the entire horizon. The coefficient suggests that a 1 percentage point higher shock leads to a 1 percentage point higher number of foreclosures.

In Figure 6b, I report the coefficients β_1^h from regressing the county-level delinquency rate on the flood damages. Again, the solid blue line reports the point estimates, and the 95% confidence interval is the dashed orange line over the horizon $h = -3 : 7$. The coefficients are insignificant for the periods prior to the shock. Following the shock, the coefficient increases to 0.025 before gradually decreasing again. The coefficients in period 1 imply that a 1 percentage point higher shock leads to a 2.5 percentage point higher delinquency rate, which given an average delinquency rate of 3.3% is an economically meaningful increase.

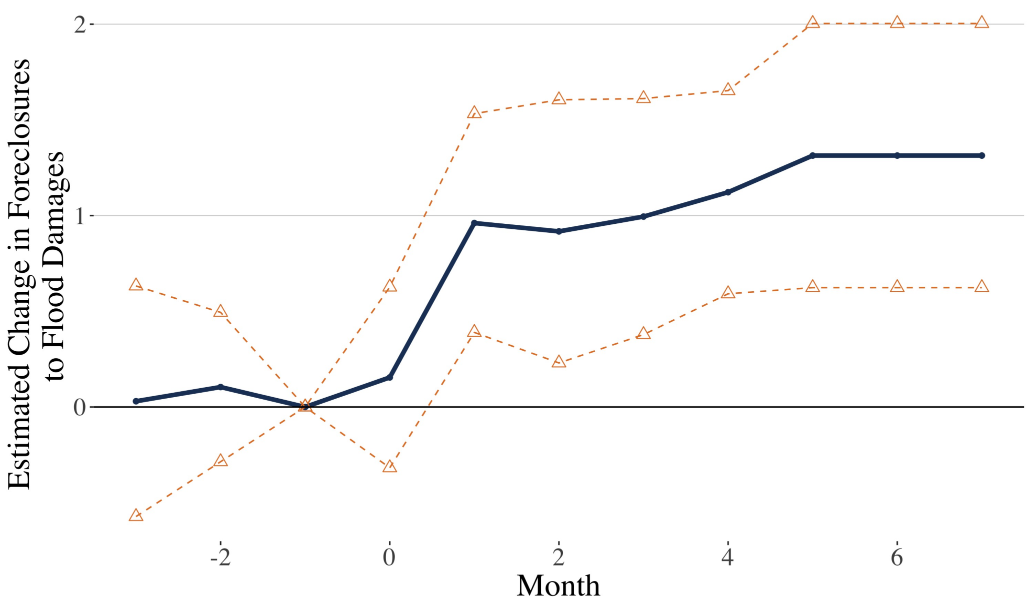
Having established a link between residential mortgage performance following natural disasters, the next step involves linking foreclosures and delinquencies to bank performance measures. To this end, I use the same delinquency data as in the previous section, namely the Fannie Mae Single-Family Loan Performance data for the years 2000 to 2020. I use balance sheet items from the FDIC SDI data as banks' performance measures. Formally, I run the following regression:

$$\begin{aligned} Y_{bt} = \beta_0 &+ \beta_1 \mathit{Market\ Exposure}_{bt} + \beta_2 \mathit{Capital\ Ratio}_{bt-1} \\ &+ \beta_3 \mathit{log(Employees)}_{bt-1} + \beta_4 \mathit{log(Assets)}_{bt-1} \\ &+ \beta_5 \mathit{ROA}_{bt-1} + \boldsymbol{\gamma X} + \epsilon_{bt}, \end{aligned} \tag{9}$$

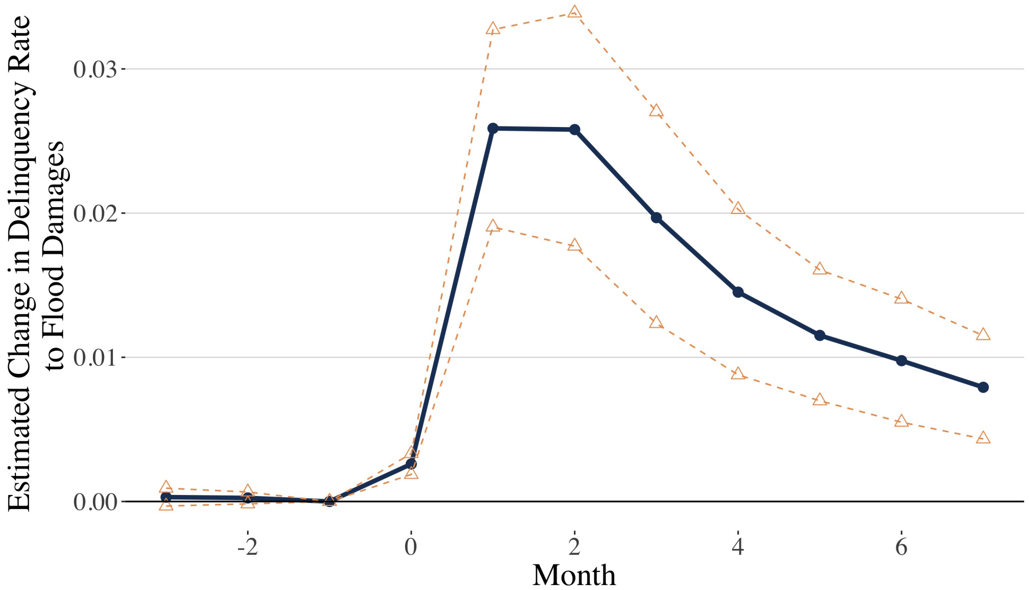
where in the baseline Y_{bt} is the return on assets available at a quarterly frequency for each bank. In the following step, I replace ROA with the capital ratio, non-performing loans, and charge-offs. The variable *Market Exposure* is either capturing the exposure to the delinquencies (*Delinquency Exposure*) or foreclosures (*Foreclosure Exposure*). Both measures are bank-level exposure measures that synthesize the exposure degree to the counties.

Panel A of Table V reports the estimates for the exposure to foreclosures. Across the four regressions, the estimates suggest that bank performance and foreclosures are negatively correlated. For return on assets and leverage, the coefficients on the exposure are negative and significant. Furthermore, non-performing loans and loan charge-offs have a positive relation with foreclosures, albeit only significantly so in the latter case.

The findings are echoed in the regression with the exposure to the delinquency rate as reported in Panel B of Table V. A 1% increase in the delinquency rate decreases returns on



(a) Mortgage Foreclosures



(b) Mortgage Delinquencies

Figure 6. Effect of flood disasters on loan performance. This figure presents the relation between bank-level exposure to current flood damages and mortgage foreclosures (Panel A) and mortgage delinquency rates (Panel B). Mortgage foreclosure data is from RealtyTrac and is available from 2004 to 2012 at the county level. Mortgage delinquency rates are computed from Fannie Mae's Loans Performance data from 2004 to 2020 at the ZIP3 level. The solid line presents the point estimates for *Flood Damages*. The short dashed lines present 95% confidence intervals on this estimate.

Table V
Bank performance and Mortgage Delinquencies

This table reports the results from the analysis of bank performance and mortgage market performance. The main explanatory variable in Panel A is the *Foreclosures Exposure*, which captures banks' exposure to local mortgage foreclosures using data from RealtyTrac for the years 2004 to 2012. In Panel B, the independent variable is constructed using delinquency data from Fannie Mae from 2004 to 2020. The county and Zip3 level data is aggregated at the bank level using a bank's mortgage lending activity. The dependent variables are one-quarter ahead measures. Leverage is based on Tier 1 capital. Non-performing loans and charge-offs are divided by the total loans. 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: Foreclosure Exposure

	ROA_{t+1}	$Leverage_{t+1}$	NPL_{t+1}	Charge-$Offs_{t+1}$
	(1)	(2)	(3)	(4)
Foreclosure Exposure	-0.027**	-0.173*	0.015	0.009***
	(-2.05)	(-1.77)	(0.606)	(4.22)
Bank Controls	YES	YES	YES	YES
Bank	YES	YES	YES	YES
Quarter	YES	YES	YES	YES
Obs.	15,566	15,037	15,566	14,429
R^2	0.501	0.886	0.854	0.496

Panel B: Delinquency Exposure

	ROA_{t+1}	$Leverage_{t+1}$	NPL_{t+1}	Charge-$Offs_{t+1}$
	(1)	(2)	(3)	(4)
Delinquency Exposure	-0.043**	-0.169**	0.069*	0.011***
	(-2.43)	(-2.15)	(1.91)	(4.20)
Bank Controls	YES	YES	YES	YES
Bank	YES	YES	YES	YES
Quarter	YES	YES	YES	YES
Obs.	15,566	15,037	15,566	14,429
R^2	0.501	0.886	0.854	0.495

assets by 4 basis points (or 10%), while leverage is 1% lower. As before, non-performing loans and charge-offs are positively related to local delinquency rates.

This short exercise provides some indicative evidence that the performance of the local residential real estate market is linked to bank-level performance. The findings are robust to using the level of delinquencies or focusing on foreclosure data.

Disentangling the residential real estate channel in its parts suggests that flood hazards can have potentially severe negative effects on bank performance.

IV. Is Exposure to High Flood Probability Priced?

In the previous section, I analyzed the effect of flood realizations on bank performance, both for balance sheet variables and for realized stock returns. In this next section, I focus on the relation between the exposure to flood risk and expected bank stock returns. I begin by evaluating the exposure to flood risk in the cross-section of stock returns. Next, I explore the time-series properties of a high-minus-low flood exposure-sorted portfolio.

A. Evidence in the Cross-Section of Returns

In this first step, I relate bank-level flood risk exposure to their corresponding stock returns in the cross-section. Formally, I estimate the following cross-sectional regression model using pooled OLS:

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 \textit{Flood Risk Exposure}_{bt} \\ &+ \beta_2 \textit{log(Assets)}_{bt} + \beta_3 \textit{log(BE/ME)}_{bt} \\ &+ \beta_4 \textit{Leverage}_{bt} + \beta_5 r_{bt-1} + \epsilon_{bt}, \end{aligned} \tag{10}$$

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 my analysis, I cluster standard errors at the bank level. Furthermore, for a fixed bank, the flood exposure only varies across time because of changing mortgage lending activity measured with HMDA data, I cannot capture the underlying flood risk by including bank fixed effects. I can however control for aggregate time-varying factors with year-month fixed effects. I replace the variable *Flood Risk Exposure* in equation 10 with a selection of different measures capturing the exposure to flood risk. The coefficient of interest is β_1.

Table VI reports the results from the regression described in equation 10 for an array of different exposure measures all capturing the same underlying risk. The main coefficient of interest is β_1, the coefficient on a bank's *Flood Risk Exposure.* All regressions control for bank characteristics and include time-fixed effects. All flood risk exposures have been standardized to facilitate comparison across specifications.

Column 1 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. This result is puzzling in light of the type of risk under scrutiny. It goes against prediction 4 in that it suggests that a high flood risk exposure forecasts a poor stock performance. This finding is in line with other papers analyzing whether markets efficiently discount physical risk from climate change (e.g., Hong, Li, and Xu, 2019).

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) I use all mortgages originated in a county to build the county exposure. 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. An additional benefit of rolling averages is that it captures general exposure to future profits from lending to a specific county for a given bank. 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. In the last column of Table VI, I run the regression using an exposure measure that 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, I divide a bank's retained mortgages by the total aggregate number of originated mortgages in that county. 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.

Table VI

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)
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**

Continued on next page

Table VI – *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)
	(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

B. Heterogeneity of Effects

As seen in Section III.B, 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 VII presents separate estimates of equation 10 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 VII 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.

Almost more interestingly, in Panel B of Table VII, I report 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.

Finally, Panel C of Table VII reports the results for the flood risk exposure-sorted samples. The estimate in column (1) is for the sample of banks with above median flood risk exposure. The coefficient on *Flood Risk Exposure* is negative with a value of -0.18 and statistically significant at the 1% level. The relation between excess return and flood risk exposure is not significant for the banks with low exposure. If anything, it would be slightly positive. This is evidence that the negative relation is driven by the high exposure banks, and does not capture bank characteristics of low exposure banks.

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.

Table VII
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**
			(-2.31)
Bank Controls	YES	YES	YES
Month FE	YES	YES	YES

Continued on next page

Table VII – *Continued from previous page*

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

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.

C. Other regional shocks

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

Panel A of Table VIII focuses on state-level controls. In column (1), I include 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 **??**. I weigh each state-level measure 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.

Panel B of Table VIII reports the estimates of four regressions including additional county-level controls. Columns (1) and (2) control 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. Controlling for flood insurance does not alter the magnitude nor significance of the estimate on the *Flood Risk Exposure*. The estimate remains at -0.16, significant at the 1% level.

Columns (3) and (4) of Panel B of Table VIII control for the county-level performance of the residential real estate market. Column (3) is estimated including the retained mortgage-weighted average of log foreclosures, and column (4) is based on log mortgage default amounts. Again, the coefficient on *Flood Risk Exposure* is unchanged.

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

D. Flood Risk Exposure Ranking and Return Predictability

Next, I sort the BHCs in quartiles according to their Flood Risk Exposure and compute the value-weighted returns of the four portfolios. Formally, I estimate the following time-series regression:

$$r_{it} - r_t^f = \alpha_i + \boldsymbol{\beta_i}'\mathbf{F}_t + \epsilon_{it}, \tag{11}$$

where r_{it} is the monthly return on the i^{th} flood exposure sorted portfolio. I control for six factors, here denoted by the vector of risk factors $\mathbf{F}_t$ and includes 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 IX reports the estimates from equation 11. 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, I proceed by splitting the sample into small and large banks. Panel B of Table IX 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

Table VIII
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. Panel A controls for state-level controls. 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: State-level Controls

	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)
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
Obs.	38,507	43,227	43,227	43,227
R^2	0.25	0.28	0.30	0.28

Panel B: County-level Controls

	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

Table IX

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

of Table IX 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.

E. The 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. I assign each bank independently 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). I use the flood risk exposures as weights to create a zero-cost high-low factor.

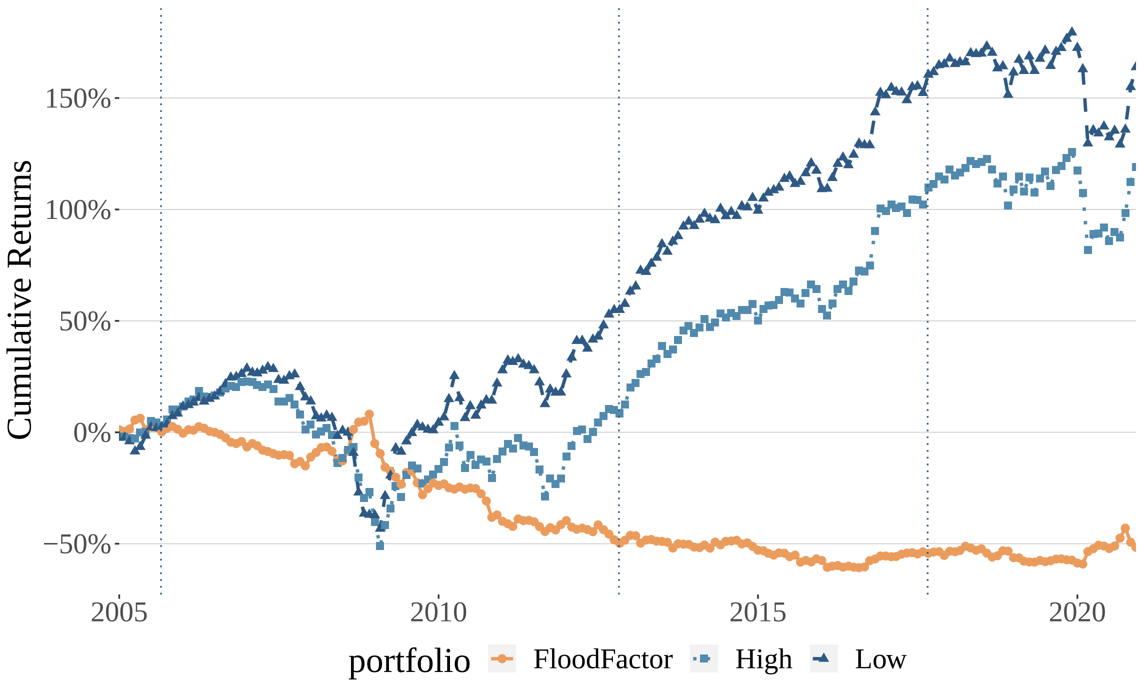


Figure 7. Cumulative Return of the Exposure-Weighted Flood Factor. The solid line plots the cumulative return of the flood factor constructed with banksf́lood risk exposure. The dotted-blue line (High) plots the cumulative return of the portfolio of banks with high flood exposure, while the dashed blue line (Low) reports the cumulative return of the portfolio of banks with low flood risk exposure.

Figure 7 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 X. This consistent under-performance of the flood factor cannot be fully explained by exposure to other factors prominent in the asset pricing literature. In column (2), I include 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.

As size heterogeneity played an important role in the previous analysis, Panel B of Table X 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 X constructs the flood factor, but only with the largest 25% of banks. The monthly return difference 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 decrease in significance could be partly explained by the reduced number of banks available to create the high-low portfolio, however, this cannot explain the change in average monthly returns. The lack of consistent return differences for the sample of large banks is consistent with the other findings based on bank heterogeneity. Exposure to floods only really matters for smaller banks.

Along the same lines, Figure 8 plots the cumulative return of the flood factor for the two size-sorted subsamples. For each sample, I compute the flood risk 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. Section V focuses on the different measures driving the negative predictability. 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%.

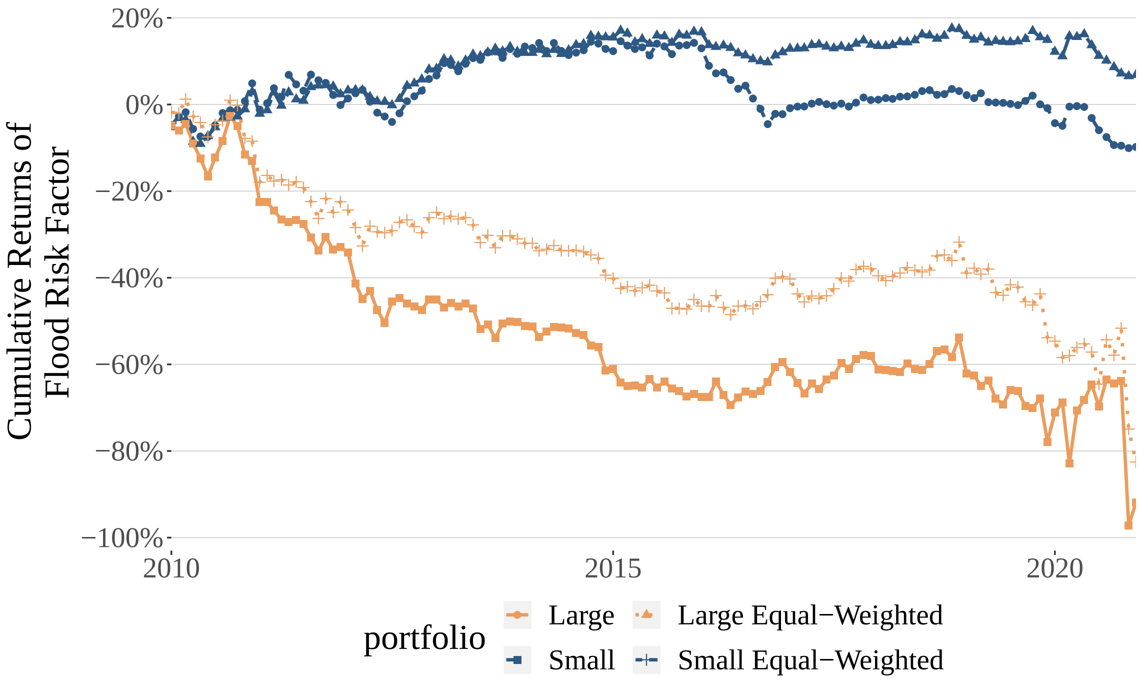


Figure 8. Cumulative Return of the Exposure-Weighted Flood Factor for Size-sorted Samples. The orange solid and dotted lines plot the cumulative returns of the flood factor from the sample restricted to small banks. The solid line is the exposure-weighted cumulative return and the dotted line is the equally-weighted returns. The two blue lines plot large banks' exposure-weighted cumulative return (two-dash) and equal-weighted cumulative return (dashed).

F. 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

Table X
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

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 12, where the orthogonalized risk factors and their related beta coefficients are given by $F^{\perp}_{T\times K}$ and $\beta^{\perp}$.

$$r_{j,t} - r_{f,t} = \alpha + \beta^{\perp}_{j} F^{\perp}_{t} + \epsilon_{j,t} \tag{12}$$

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:

$$R^2 = \sum_{k=1}^{K} DR^2_k, \text{ where } DR^2_k = \left(\hat{\beta}^{\perp}_{k} \frac{\sigma_k}{\sigma_r}\right)^2 \tag{13}$$

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:

$$F^{\perp}_{T\times K} = F_{T\times K} S_{K\times K} \tag{14}$$

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.[7]. 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 9. 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

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

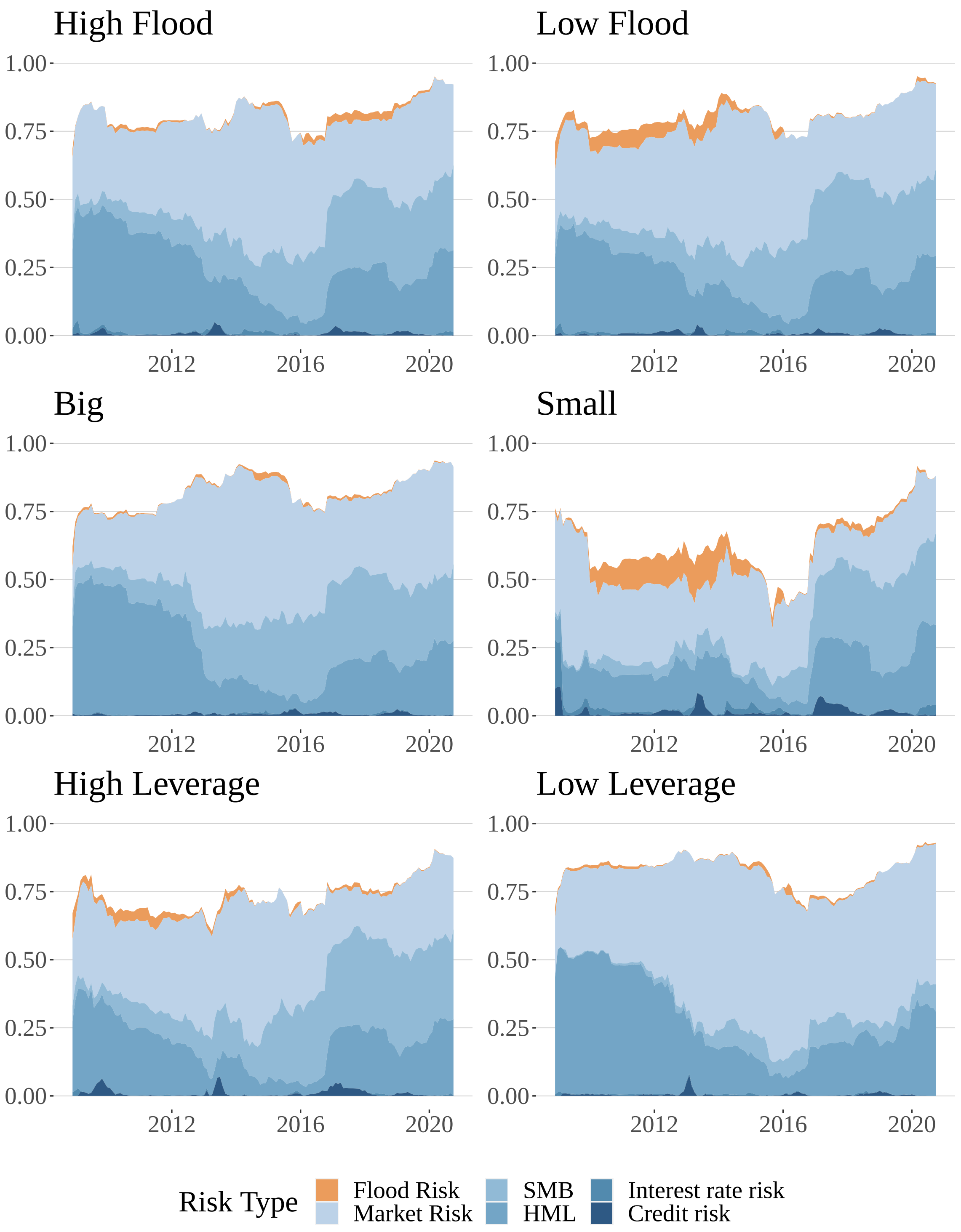


Figure 9. Variance Decomposition. Rolling variance decompositions for US bank portfolios. This figure shows variance decompositions for portfolios of US banks depending on bank characteristics. In the first row, the graphs plot the variance for the portfolio divided along their flood risk (above and 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.

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 9 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 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.

V. What Drives the Flood Discount?

In the previous section, I used realized returns as estimates for the expected returns of bank stocks and the flood factor. However, realized returns can be affected by unanticipated shocks, which biases their use as estimates for expected returns. So in this section, I focus on the potential drivers of the negative stock performance of exposed banks.

A. *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 flood realizations. 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 correlated with contemporaneous flood disasters and picking up these negative (unanticipated) shocks. This in turn could explain the negative coefficient on the flood risk exposure uncovered in the previous section. So, using the estimates for property damages from floods provided by SHELDUS, I control for current disasters by including *Damage Exposure* from equation 2 to the regression framework. Formally, I run the following regression:

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 \textit{Flood Risk Exposure}_{bt} + \beta_2 \textit{Flood Damages}_{bt} \\ &+ \beta_3 \textit{Flood Risk Exposure}_{bt} \textit{Flood Damages}_{bt} \\ &+ \beta_4 \textit{log(Assets)}_{bt} + \beta_5 \textit{log(BE/ME)}_{bt} \\ &+ \beta_6 \textit{Leverage}_{bt} + \beta_7 r_{bt-1} + \epsilon_{bt}. \end{aligned} \tag{15}$$

Additionally, I include the interaction term between the disaster realization measure and the exposure to risk, which allows me to capture offsetting forces separately.

Table XI reports the estimates from equation 15 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 XI 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. The coefficient on the flood damage exposure is also negative and significant in all specifications, which is in line with the findings from the previous section. 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 I focus on the subsample of small banks. The estimates are reported in Panel B of Table XI. 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. Again, the interaction term is insignificant.

Finally, for completeness, Panel C of Table XI reports the estimates for the sample of large banks. As before, the flood risk exposure has no explanatory power. Exposure to disaster is however associated with a decrease in realized returns.

Taking this one step further, Table XII reports the results for four samples of the data. Again, the key assumption to test is that flood disasters are the main driver behind the negative coefficient on the flood risk exposure. The previous table, Table XI is the first

Table XI
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)
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***	

Continued on next page

Table XI – *Continued from previous page*

	(-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 XII
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
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

Continued on next page

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

evidence that this assumption does not hold. In the next step, I replicate the baseline result but removing periods with flood disasters. First, I exclude major disasters from the sample. In column (1) of Table XII I remove the months after Hurricane Katrina. Specifically, I delete data from August, September, and October of 2005. Column (2) removes other major storms (e.g., Hurricane Sandy and Hurricane Harvery). Second, I limit the sample to banks unaffected by any disasters. Column (3) restricts the sample to bank-months with zero exposure to flood disasters, 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. 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 results suggest that for the sample of small banks, exposure to flood realizations cannot explain the negative coefficient on the exposure to flood risk. However, this does not mean that the exposure does not matter, as seen by the significant coefficients. It simply states that other factors are driving the underperformance.

To complement Table XI, I estimate how much of the return variation of the flood factor is attributed to flood damages. Formally I run:

$$r_t^{FF} = \alpha + \beta \mathit{Flood\ Damages}_t + \epsilon_t, \tag{16}$$

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.

The estimates for the full sample of banks are reported in Panel A of Table X. Again, I use three different measures of damage exposures. 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 X 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.

B. Reaction to Climate Change Concerns

Investor preferences change when new information becomes available. As pointed out by Pástor et al. (2021), climate change concern is a relatively new phenomenon and is therefore likely to affect 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.

In this section, I test this hypothesis by controlling for climate change attention and knowledge. First, I download frequency data from Google Search Volume Index (SVI) for the topic of climate change and floods more specifically. I restrict the search to U.S.-based users. This data is a proxy for widespread awareness about climate change and its potential effects. It is available since 2004 and I aggregate it 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).[8]

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

Table XIII
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

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, I will also show results for an index focused on flood-related concerns, climate summits, and global warming separately. This allows disentangling concerns about physical risks from transition risks.

The estimates from these regressions are reported in Table XIV. 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 XIV 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 XIV. 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 fails to explain the negative return predictability of flood risk exposure.

VI. 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 to

Table XIV
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

construct 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 an array of different performance measures. Not only do loan charge-offs increase, but profitability decreases for up three quarters. Furthermore, I find that disasters have large negative impacts on household delinquencies and foreclosures which have direct spillovers to bank operations. Together with the projected increase in severity and frequency of flood disasters, this suggests that the negative impact of floods is going to become worse.

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 sizable for this group. On average, a one-standard-deviation increase in exposure results in a 30 bps lower monthly 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.

In a third contribution, I decompose the return variation of different groups and find that the exposure to flood risk explains only a very little share of the variation, suggesting that the risk stemming from the exposure is not very large.

In a final contribution, I shed light on the channels through which the flood risk exposure negatively relates to the bank stock returns. First, I show that past disaster realizations cannot fully explain the negative predictability. While flood disasters lead to weaker stock performance, the negative relation of flood risk exposure remains. Second, I find no evidence that the effect is entirely 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. Further, I find that the direct risks from floods are only priced once the risks become imminent. The results on the cyclicality of flood damages suggest that financial investors are somewhat myopic in that they only focus on flood risks that have immediate financial effects.

The results suggest that banks are negatively affected by flood realizations, but that investors do not directly or fully 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.

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.

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.

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.

Duan, Tinghua, Frank Weikai Li, and Quan Wen, 2021, Is Carbon Risk Priced in the Cross Section of Corporate Bond Returns?, Working Paper.

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.

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.

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.

Lagarde, Christine, 2021, Climate Change and 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 US 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.

Noth, Felix, and Ulrich Schüwer, 2018, Natural Disaster and Bank Stability: Evidence from the U.S. Financial System, Working Paper.

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.

Pachauri, R. K., and Leo Mayer, 2015, Climate change 2014: synthesis report, Intergovernmental Panel on Climate Change.

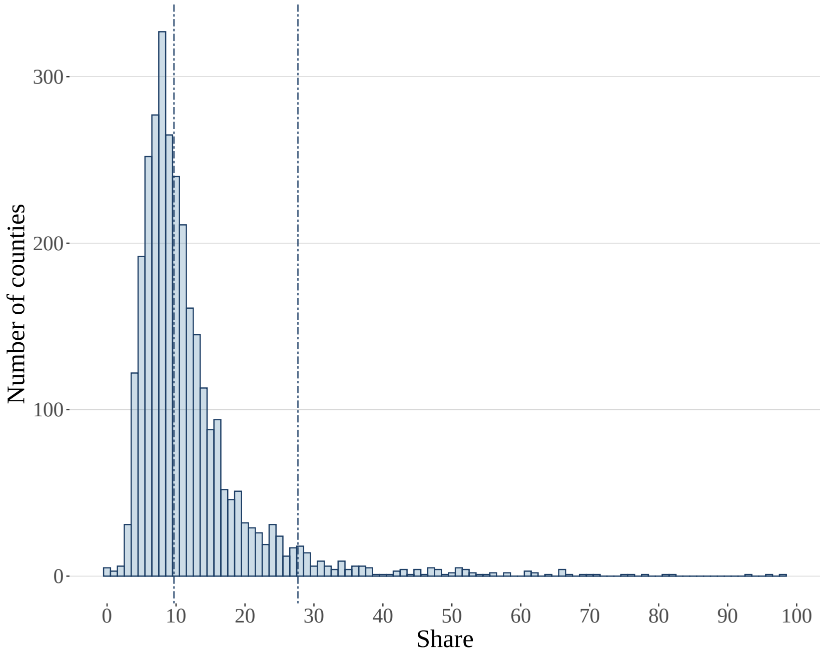
Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Dissecting Green Returns, Working Paper.

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

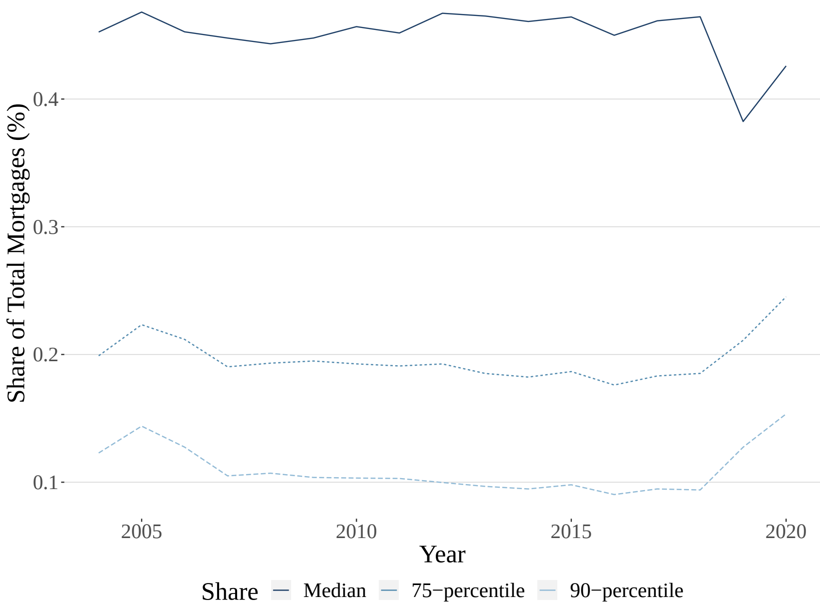
Rehbein, Oliver, and Steven R. G. Ongena, 2020, Flooded through the Back Door: The Role of Bank Capital in Local Shock Spillovers, Working Paper.

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.

AI. Additional Figures



(a) Number of Counties by Risk Group



(b) Share of Mortgage Amounts by Risk Percentiles

Figure AI.I. 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.

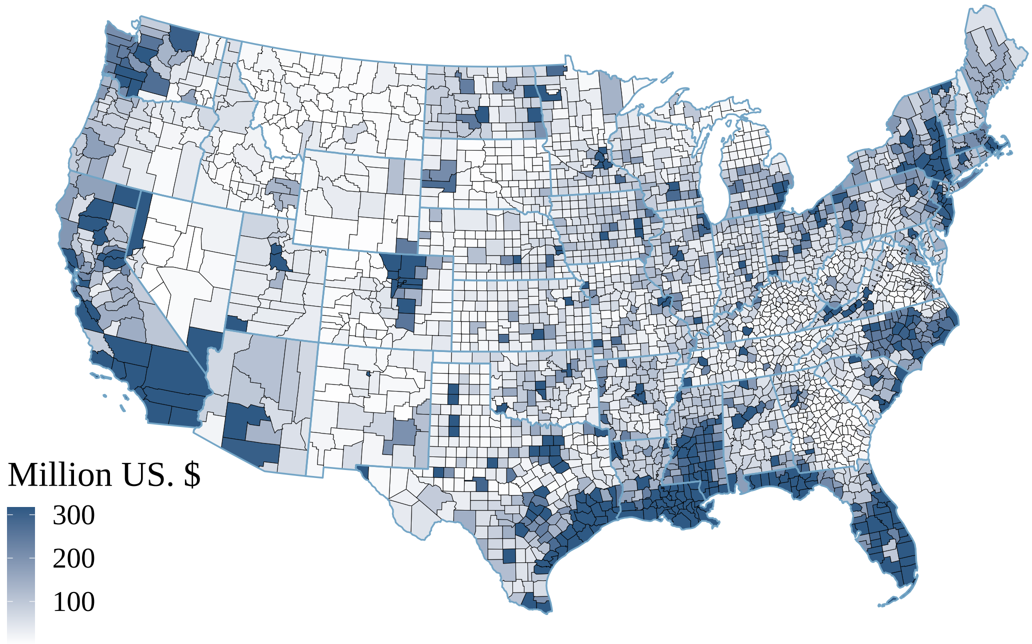


Figure AI.II. Property Damages from Floods. This figure plots the estimated property damages from floods since 1960 in the United States. The estimates come from SHELDUS and are available at the county level.

AII. Principal Component Analysis

In section IV, 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 AII.I 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 AII.I
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 (1)	PC2 (2)	PC1 (3)	PC2 (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%

AII.A. Constructing the PC Loadings

The loadings from the principal component analysis reported in Table AII.I 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 ($\hat{\boldsymbol{\lambda}}_2$. 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:

$$r_t^i - r_t^f = \alpha^i + \beta_{PC}^i R[PC2]_t + \boldsymbol{\beta}^{i'} \mathbf{F}_t + \epsilon_t^i \tag{AII1}$$

The results from this regression for value-weighted and equal-weighted portfolios are reported in Panel A and Panel B of Table AII.II respectively. Compared to the results from Table IX, 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.

AII.B. Time-Series Dynamics

Next, similar to Figure 9 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

Table AII.II
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 $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

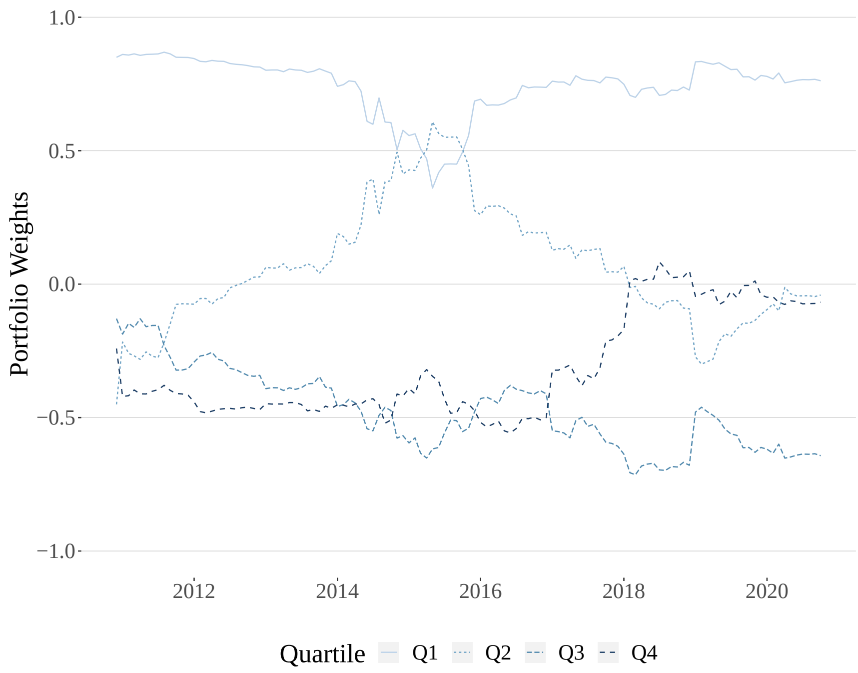
Panel A: Value-Weighted

	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

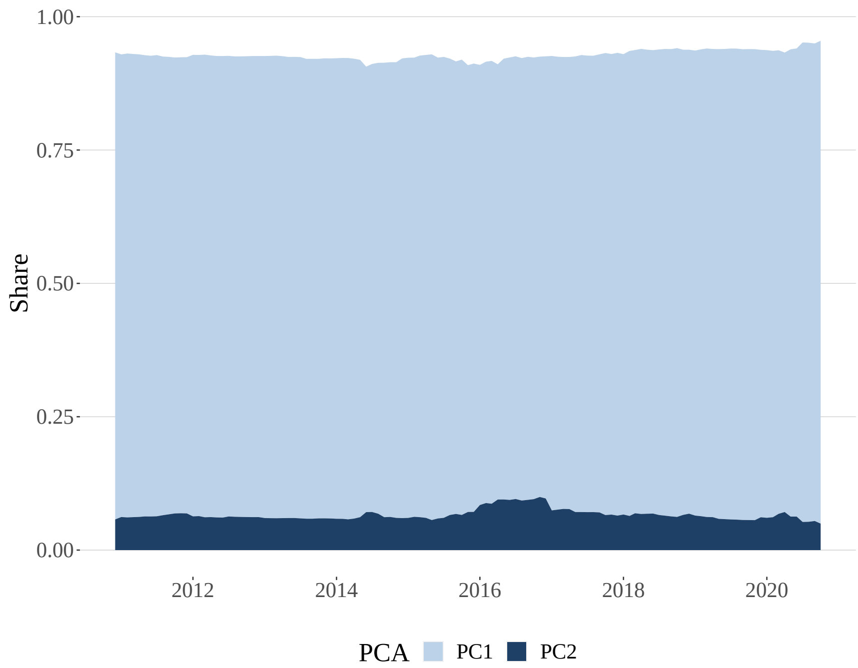
Panel B: Exposure-Weighted

	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

for the four flood risk sorted portfolios and the proportion of the variance explained by the first two principal components. Figure AII.III 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 AII.IIIb. 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 **??**. 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).

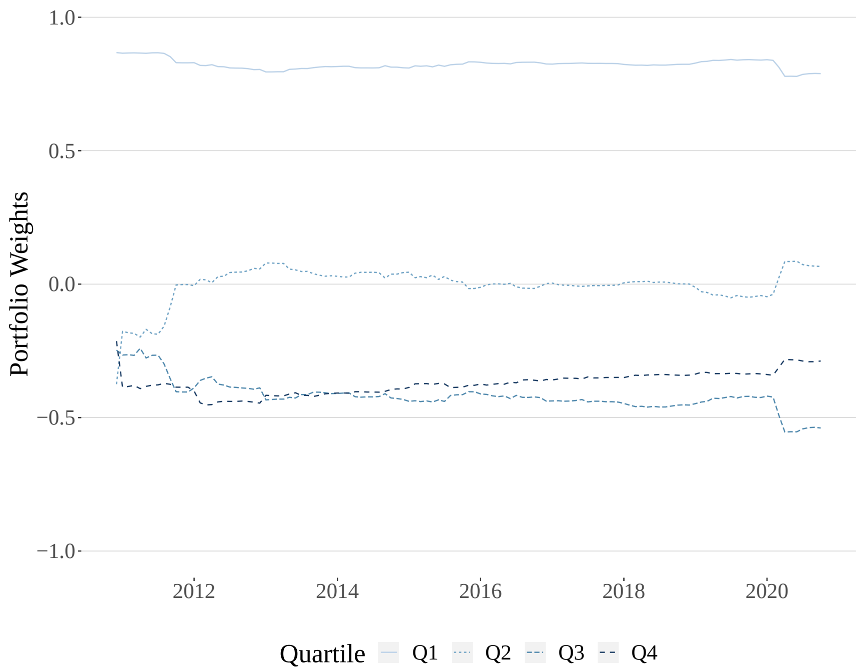


(a) PCA Weights

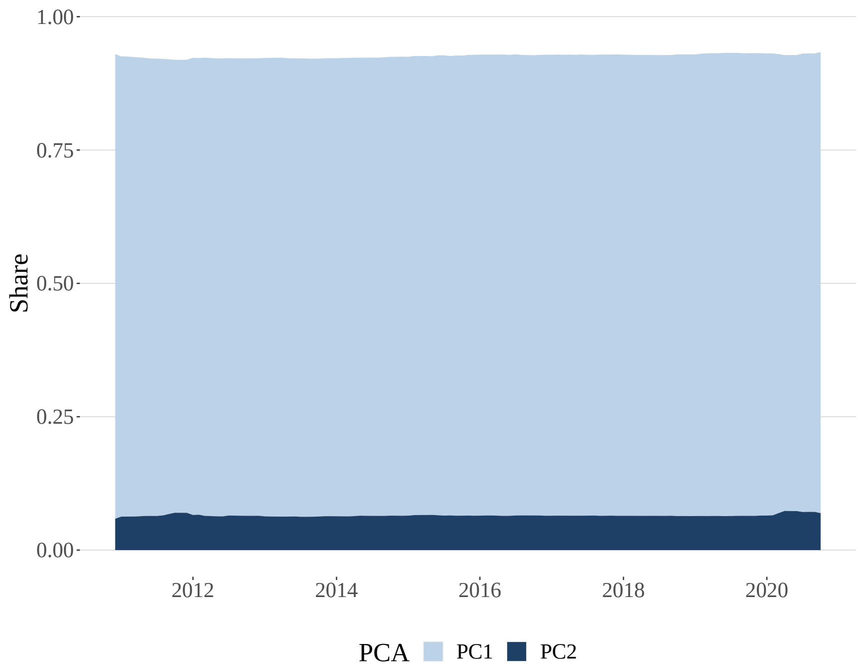


(b) Variation in Returns

Figure AII.III. 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 AII.IV. 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.

AIII. Framework

I set up a simple model to guide the empirical analysis and clarify the key economic relationship between bank profitability and exposure to flood risk. Consider a discrete-time economy with a competitive and arbitrage-free banking sector. Each period, banks have one-period investment opportunities, that is, investments made in period t pay off in period $t+1$.

In each period, the economy is in one of two states: a normal state n or a disaster state d. The disaster state is characterized by a flood disaster of intensity σ. Banks invest in mortgages and the investment opportunities differ in their exposure to flood risk. Borrowers repay Y in good times and 0 if they are hit by a flood in the bad state of the world. Let θ be the share of the bank's loan portfolio exposed to flood risk. For now, I assume that θ differs across banks, but remains constant over time for a given bank. I assume that a single investment has a flood risk exposure of either 0 or 1. This can be viewed as a house being located outside or inside of a flood plain. However, this does not mean, that a house with exposure 1 is necessarily destroyed if a flood occurs. This information is given by the disaster intensity. We can think of σ as expressing the share of the housing stock with risk exposure 1 being destroyed by a given disaster. This implies that given a housing stock H with $\bar{\theta}$ located in flood plains, following a disaster with intensity σ, $\sigma\bar{\theta}H$ houses are destroyed with borrowers defaulting and repaying 0.[9]

Figure AIII.V depicts the stylized balance sheet of a bank with zero exposure and θ exposure. Given the riskiness θ of a bank's portfolio of assets and the shock S, the gross portfolio income is $Y(\theta, \sigma)$.

The bank finances itself through deposits, D, that can be viewed as one-period risk-free debt. Hence, a unit of deposit pays $1 + r^f$ at $t + 1$, where r^f is the risk-free rate. For deposits to be risk-free, I further assume that the debt payments $(1 + r^f)D$ promised at $t + 1$ is smaller than the portfolio income, or formally

$$D \leq \frac{Y(\theta, \sigma)}{(1 + r^f)}$$

In a period of disaster, the bank's payoff is defined as

$$Y^d(\theta, \sigma) = (1 - \sigma\theta)Y,$$

and the normal time payoff is defined as Y.[10]

[9]The market share of a bank can be viewed as being also being included in θ. I assume that the probability of being affected by a flood is equal for all houses located in the flood zones.

[10]This is a clear simplification; if I pursue the model part further, I will have to adapt this. Banks with a higher θ are riskier, hence if the risk is known, then payoffs in normal times should increase with θ.

Net income is given by:

$$\begin{aligned} Y^d(\theta, \sigma) - (1 + r^f)D \\ (1 - \sigma\theta)Y - (1 + r^f)D. \end{aligned}$$

So bank profitability defined as return on equity is given by:

$$\begin{aligned} r_E^d &= \frac{(1 - \sigma\theta)Y - (1 + r^f)D}{1 - D} - 1 \\ &= \frac{(1 - \sigma\theta)Y - 1 - r^f D}{1 - D} \end{aligned}$$

Thus, the bank's equity return in the bad state is negatively related to the size of the shock, and the share of exposed loans. Further, banks without any exposure are not affected by natural disasters.

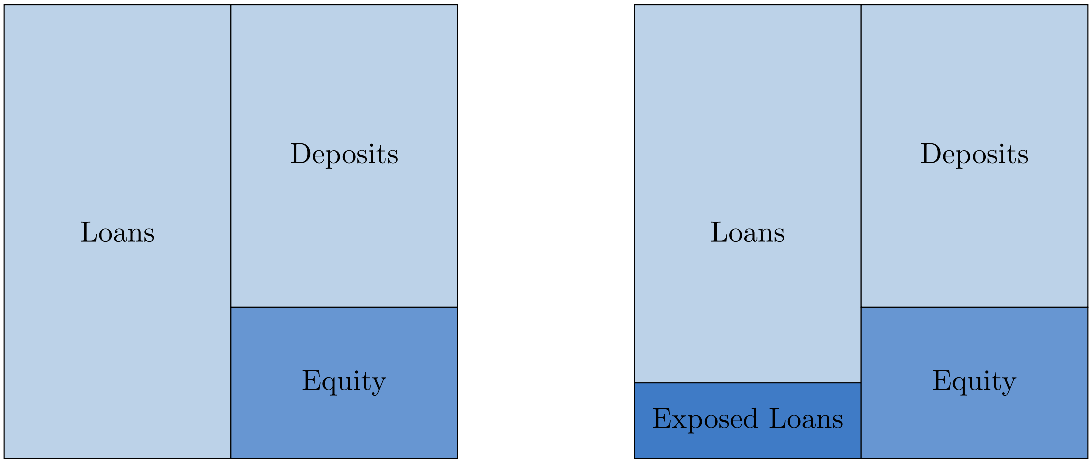


Figure AIII.V. Bank Balance Sheet This figure depicts the stylized balance sheet of a bank without any loans exposed to flood risk (left) and a bank with a share θ of its loans exposed.